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Total cost of ownership optimization model for battery-electric trucks

Supporting decision-making on battery-electric trucks

Master's thesis in Management and Economics of Innovation & Supply Chain Management

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Cover: Picture of electric trucks from Volvo (Volvo Truck Corporation, 2021).

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Abstract

As electric trucks are relatively new to the market, buyers' purchasing processes are not used to evaluate electric trucks and manufacturers want to facilitate the adoption. A total cost of ownership (TCO) is often used to evaluate investments, thus sellers can promote the most cost efficient electric truck to the customer by analysing TCO. This thesis seeks to create a TCO optimisation model to select a truck variant with the lowest TCO based on vehicle routing, energy consumption and heterogeneous fleet.

To create the TCO model, a literature review and a commercial study were conducted. In parallel, data was collected from internal meetings, the literature and desk research. From the data collection, it was concluded that a single model would not be able to account for different customers' needs. Three models were built: a heterogeneous electric vehicle routing problem with time windows (HEVRPTW) formulated as a mixed integer programming (MIP) model, a hybrid model, composed of a VRPTW MIP and a spreadsheet, and an ant colony optimization (ACO) model.

Three realistic cases were built to validate the model, analyse the TCO and the selection of electric trucks and assess the supply chain impact. Then, a sensitivity analysis of the TCO is performed. The results show that driver cost and initial cost have the most impact on TCO, whereas energy cost increases with mileage. The supply chain is heavily impacted by the battery size as there are trade-offs when changing the battery capacity. The optimal battery capacity is a combination of the energy required and the charging strategy.

Keywords: Total cost of ownership (TCO), Electric truck, BEV, Optimization, Ant Colony, Vehicle routing, Heterogeneous fleet, Purchasing process

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Henrique Geromel Dotto & Kristinn Thor Magnússon

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Contents

List of Acronyms

Below is the list of acronyms that have been used throughout this thesis listed in alphabetical order:

ACO	Ant Colony Optimization
BEHV	Battery-electric heavy vehicle
BEV	Battery-electric vehicles
EOL	Battery end of life
ePTO	electric power take-off
HEVRPTW	Heterogeneous electric VRP with time windows
ICEV	Internal combustion engine vehicle
OEM	Original equipment manufacturers
SOC	State of charge
SOH	State of health
TCO	Total cost of ownership
TSP	Traveling salesman problem
VRP	Vehicle routing problem
VRPTW	Vehicle routing problem with time windows

List of Figures

List of Tables

1

Introduction

1.1 Background

The battery-electric truck, or battery-electric heavy vehicles (BEHVs), have zero tail-pipe emissions that can help to decrease pollution from road transport which is a problem, especially in big cities. Diesel trucks are currently the most widely used and BEHVs are rather new to the market. Hence, the purchasing of a BEHV requires the decision of new specifications which are unfamiliar for most businesses and bring challenges such as vehicle range and high initial costs (Morganti & Browne, 2018). For most businesses, this process either leads to a *new task* purchasing situation, where the buyer is unfamiliar with both the product and supplier or a *modified rebuy* where the buyer is purchasing from a known supplier (Weele, 2018). A concern for purchasers in those situations is that there is high uncertainty of the outcome for *new task situation*s and moderate uncertainty for *modified rebuy* (Weele, 2018).

To reduce the uncertainty of the outcome, the focus should be on the total cost of ownership (TCO) instead of the initial price (Weele, 2018). In fact, one of the benefits of TCO is being able to justify higher initial prices with long-term cost-effectiveness (Ellram, 1995). The TCO method is done from the purchaser's standpoint and calculates costs related to purchasing processes, installation, operation, and disposal of the truck (Saccani et al., 2017). However, the calculation of TCO for battery-electric trucks (BEHVs) is not straightforward.

Many factors can affect the BEHV's TCO, but the energy consumption is a central one (Delucchi & Lipman, 2001). Different battery sizes can affect the energy consumption due to changes in vehicle weight, while the average speed, road hilliness, traffic and weather can also affect the energy consumption, to mention just a few (Delucchi & Lipman, 2001; Ghandriz et al., 2020b; J. Wang et al., 2018). Policies around BEHVs can change between different locations and over time, which alter the ownership and purchasing costs. The resale price (if any) is hard to predict as it depends on several factors and there are uncertainties with the second-hand market of electric vehicles (Sandén & Wallgren, 2017).

1.1.1 Volvo Trucks

Volvo Trucks sells BEHVs and offers a service, electromobility made easy, which provides a customised solution to their customers' needs to support electromobility adoption (Volvo Trucks, 2019). Volvo provides expertise, guidance & technology, and recommendation for technical components to optimise the TCO, making it predictable for the customers. There are many variables and uncertainties in the calculations of TCO and Volvo is looking to make the models even more accurate.

Volvo currently offers in Sweden two types of medium-duty electric trucks, FL and FE Electric, and three types of heavy-duty electric trucks, FH, FM and FMX electric (Volvo Trucks, 2022a). Both those types of trucks will be referenced as BEHV in this paper. For each truck, there can be variants such as the number of battery packs, different axle configurations based on application, and a different number of electric motors for the heavy-duty trucks (Volvo Trucks, 2022a). Each of the models is intended for a certain range of use but the truck can be customised for the customer's needs and specifications. All those decisions must be made in the selling/purchasing process.

For Volvo to optimise the TCO for an incoming customer, Volvo needs to receive specifications and operation data from the customer. The customer could additionally list some minimal performance measures that the operation of the truck would be expected to reach as Volvo considers the whole scope (Volvo Trucks, 2022b).In many cases, operations of BEHVs have needed route tailoring and daytime charging (Hovi et al., 2020). The route tailoring or optimisation used for the TCO model is a service that Volvo offers to support the customer (Volvo Trucks, 2022b). From the TCO model, Volvo can further recommend and specify which truck will fulfil the customer's needs the most (Ellram, 1994), leading to a higher customer satisfaction.

1.2 Aim and scope

This project aims to create a TCO model for Volvo to assist the decision of selecting an electric truck that suits the customer's need. A set of four sub-aims and respective research questions need to be addressed to achieve the defined aim:

1. Explore TCO models in literature and their impact on purchase decision-making

    RQ.1. What are the main dimensions of TCO of BEHVs?

2. Understand Volvo's business context associated with BEHV sales and create the TCO model

    RQ.2. What are the most relevant analytical models present in the literature to build an accurate TCO model that suits Volvo's context and customers' specific needs?

3. Acquire and interpret the data required to perform a TCO analysis

    RQ.3. What is the minimum information needed from the customer to calculate a reasonable accurate TCO?

4. Perform a scenario analysis of different applications with the proposed TCO model

    RQ.4. What parameters affect the most the TCO calculation of BEHV?

    RQ.5. How is the proposed TCO model able to assist Volvo in helping customers to have a smooth transition to electromobility regarding supply chain impact?

2

Methods

This chapter presents the methodological structure of this work. To answer the research questions in 1.2, the development was divided into four parts: literature review, data collection, models' formulation, and analysis. The first two parts gathered the information required to develop the TCO conceptual model. Then, it was translated and formulated into a mathematical model. Lastly, different cases were created to validate the model and discuss the results.

2.1 Literature review

The first objective was to provide the theoretical base for the project. In order to get an overview of research done on TCO, the Scopus database was used to map the research up to 2022. A literature study was conducted on the subjects to understand the use and application of TCO models for electric trucks to grasp what was needed for the project and what methods have proven to be effective for similar projects. The keywords that were searched for were "TCO models", "Electric Trucks", "TCO calculation", "TCO simulation", "TCO optimisation", "Logistics performance", and their combination. An additional literature search was conducted throughout the project when new literature was needed on a specific subject. In the end, a theoretical TCO model was created to summarise the findings from the literature.

2.2 Data collection

The project had some characteristics of action research. It aimed to design solutions to an organisation's real problems, it was iterative, going from problem identification to solution evaluation, and it intended to contribute to both theory and practice

(Argyris et al., 1985). That said, a diary was used to register the activities within Volvo, as field notes (Bell et al., 2019). Spontaneous meetings were held continuously at every opportunity with a contact at Volvo to acquire information about Volvo's needs, procedures and available data. In instances the contact did not have knowledge or access to this information, a meeting was scheduled with relevant personnel. The personnel at Volvo in the meetings had either a technical background or a business background. Throughout the whole process, 24 meetings for a total of almost 13.5 hours were held.

For the TCO model to be supportive of Volvo's selling process, the model needs to handle possible input data that Volvo's sales personnel usually have access to during the selling process. Volvo receives from the customer certain information whereas Volvo gets back to the customer with information that should support their needs. These insights were valuable to decide the model structure. Besides, Volvo was already calculating energy consumption based on customer data. With that, the model could skip energy calculation for routes, taking them as input instead.

Information on the usage and structure of a TCO model was acquired by a literature review (see Section 3). Research on electric vehicles or related subjects was analysed regarding if they were meaningful or not for the project. Information from at least two researches was used to back up a model decision. Sole research was only used if no other related research was found, but still meaningful.

On top of the Volvo context and literature review, the market context was also taken into consideration to fill gaps. Desk research was done to grasp commercial perspective and understand the thoughts and behaviours of companies and customers in the industry (Zaltman, 1997).

The information from the meetings was in form of notes and was assessed afterwards. Then, a decision was made on how it could be integrated into the model. If needed, a reasonable simplification was made to introduce the requirement in the model. The assessment of what information to use directly was based on how other authors in the literature handled similar information in other research (see Section 3) or how it was done commercially by similar tools (see Section 4.2).

2.3 Model formulation

The model started from the simplest formulation and was developed following a logical order based on previous studies. At each development step, the model formulation present in the literature was evaluated, and the best fit was selected and integrated within the so far developed model. Then, the model was reviewed and validated.

It is widely discussed in the literature that a Vehicle Routing Problem (VRP) (see section 5.1.1) and its extensions become extremely difficult to find an optimal solution in a reasonable time as its size grows. This was also true for the proposed TCO optimisation model in this work. Therefore, besides the general model, three alternatives were developed: a simplified model, a hybrid model using a spreadsheet, and a heuristic model. Most of the time, the solutions found by the alternative models are not optimal but are reasonably close to the optimal solution to support decisions.

2.3.1 Complete model

The model was formulated as a mixed-integer (linear) programming (MIP). Linear programming is a method used to minimise or maximise the desired outcome which is subjected to a set of linear constraints (Britannica, 2017). Hence, the two main components of a linear programming problem are exemplified with the objective function (2.1), which minimise or maximise the outcome, and the constraint (2.2).

$$Min/Max \;\; c_1x_1 + c_2x_2 \tag{2.1}$$

$$a_1x_1 + a_2x_2 \leq b_1 \qquad \forall x_i \geq 0 \tag{2.2}$$

In case all variables declared on the linear programming problem are integers, it is defined as integer programming. Similarly, if there are both integer and continuous variables, it is defined as MIP. In order to solve this mathematical problem, the AIMMS software was used. This software can solve a large variety of linear programming problems, from the simplest to non-linear and quadratic problems. The solver used to optimise the MIP was CPLEX from IBM ILOG (AIMMS, 2020).

The model was divided into two parts: the *routing model* and *the cost model*. The *routing model* encompasses the mathematical formulation of the truck operation. This is the main part when choosing the technical specifications of the vehicle. The *cost model* encompasses the monetary representation of the operation together with all the cost parameters presented in the conceptual model (section 4.3). Lastly, the model was constantly reviewed and validated at every step through peer review. In order to validate the output, data of a feasible problem was used together with cost data from the literature.

2.3.2 Alternative models

From the complete model, it was possible to identify some simplifications that would lead to faster results. The first alternative is the general model modularised into part of the complete model with great computational effort. By experimenting with the routing problem in question, it was identified that some parts of the model could be removed with little effect on the result. The second alternative is a straight simplified model combined with a Microsoft Excel spreadsheet model. The last alternative is a heuristic model using an Ant Colony Optimization (ACO) algorithm (see section 5.1.2). These methods are presented in this work as possible alternatives to deal with larger problems that the complete model is not able to finish in an acceptable time. Thus, the models are used to compare outputs, not to compare their computational efficiency.

2.4 Analysis

In order to exemplify the complete model potential and find how different variables affect the TCO calculation, three realistic cases inside Sweden were created: urban distribution, regional distribution and long-haul distribution. The validation of the model helped determine how well the model could account for the variety of Volvo's needs. The data gathered for the cases, therefore, needed to be realistic and reflect a possible real-world case that Volvo could face (Table 6.1). This analysis of the variables that affected the TCO model the most was intended to help Volvo assist its customers with the transition to electromobility. It will be possible to understand the monetary impact of each decision.

The urban distribution case was inside the great Gothenburg area where numerous customers and charging stations were selected and added as an input to the model. The regional case had a few customers and charging stations in Skåne county in Sweden. The long-haul distribution was between Gothenburg and Stockholm where there were customers and charging stations along the way. The cases helped to high-light the input parameters that affected the results the most in different situations and what truck variants are suitable in what context.

Sensitivity analysis was conducted on key parameters and outputs. The sensitivity of the TCO was analysed by decreasing and increasing each parameter by 20% and keeping other parameters fixed. The goal of this analysis was twofold. First, to detect the parameters that had the highest impact on TCO. Second, to see if the TCO was sensitive to the selected model's parameters and outputs.

To ensure the reliability of the results, the data required to run the complete model was taken from real-world applications and the most recent research. All values and their sources were discriminated as well as the assumptions made. The data gathering of input is presented in the section 6.1. To demonstrate the validity of the results, the outputs of the complete model are compared with the alternative models for each case.

3

Literature review

This chapter focuses on exploring the theoretical background required for this thesis and it is divided into six parts. First, an overview of the research on TCO is presented. Second, general models for TCO are introduced. Third, different TCO models for battery-electric vehicles (BEVs) are presented, highlighting their unique contributions to the field. Fourth, specific models for energy consumption prediction are presented, as they are relevant for defining the truck specifications. Fifth, the impacts on the supply chain from using a BEHV are discussed. Sixth, the differences in the purchasing processes of BEHVs are shown. Lastly, the findings regarding TCO for BEHVs are summarised.

3.1 Background on TCO research

When searching for "Total cost of ownership" as a part of the title, abstract and keywords, the database returned around 2500 results (February 2022). The two oldest papers on TCO are from 1969 and are both on engineering subjects. The first paper assessed the reliability of life cycle cost (concept related to TCO) while the other used TCO to assess the cost of using different technologies. The Figure 3.1 shows the evolution and trend of papers published each year about TCO in the Scopus database.

From 1969 to 1994, there was limited research on TCO ranging from zero to seven published papers per year. The majority (50.8%) of studies were engineering-related while other articles are classified in numerous subject areas. The two by far most cited papers in this period, both by Ellram, were about the TCO as a tool: one gave a framework for TCO while the other discussed the elements and implementation of TCO.

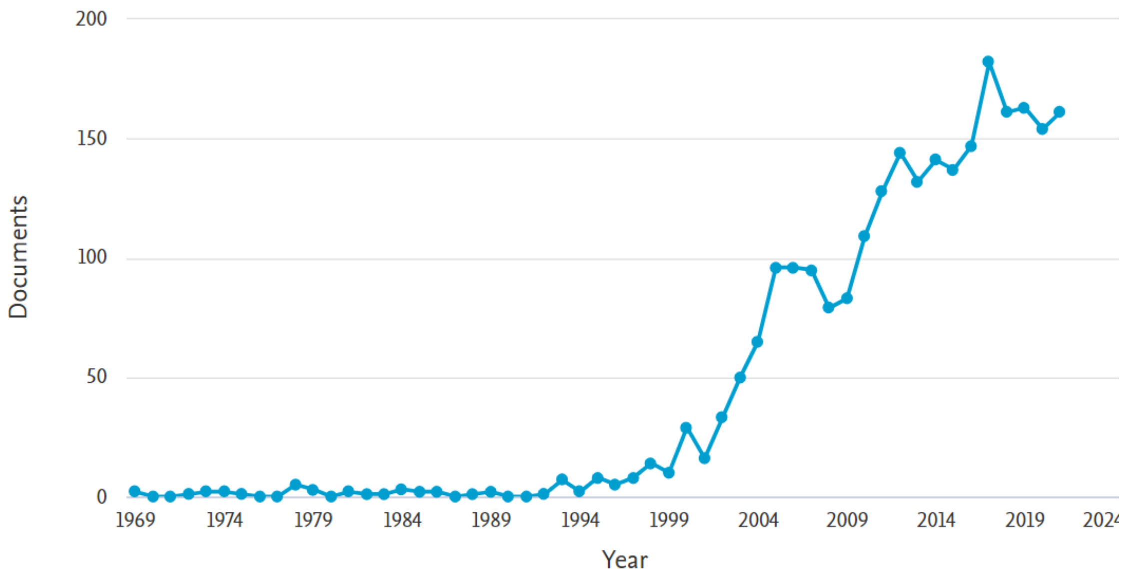

Figure 3.1: Number of papers published in Scopus database regarding TCO by year until 2021.

From 1995 to 2017 there was an escalation in the number of papers about TCO, going from 8 papers per year (in 1995) to 172 papers (in 2017). Most of them were classified as engineering (31%) and computer science (22%) subjects. There are numerous highly cited papers (>200) in that period. The topics of the papers to mention are cloud computing, vehicle electrification, power management and supplier selection. All these papers mentioned have in common that the TCO calculations are used to compare a new method or product to the currently widely used.

From 2018 the number of papers about TCO has been similar in quantity but their share related to energy (7.2% to 13%) and environmental science (3.3% to 8.1%) increased while the share of papers regarding engineering and computer science subjects decreased by 10% combined. The five most cited articles from 2018 are all related to electric vehicles where TCO is used to evaluate their possible adoption. Table 3.1 shows the two most cited papers from each of the periods considered here. The electric vehicle is among the most popular subjects and many highly cited papers commonly use TCO to assess new technology.

"Technology" (or "technologies") is mentioned in 1/3 (863 papers) of the papers in the database along with TCO. Interestingly, the trend in the number of papers published each year, which mention both TCO and technology, resembles the one shown in Figure 3.1. A TCO seems to be often used by researchers to assess the cost of technologies but also to evaluate suppliers, among other objectives. Related

Table 3.1: The two most cited papers from each time periods of TCO literature analysed.

Title	Year	Cited by
Cloud computing - Issues, research and implementations	2008	441
Vehicle electrification: Status and issues	2011	380
Total cost of ownership and market share for hybrid and electric vehicles in the UK, US and Japan	2018	200
Adoption of electric vehicle: A literature review and prospects for sustainability	2020	121
Total Cost of Ownership: Elements and Implementation	1993	99
A Framework for Total Cost of Ownership	1993	53

to technology, electric vehicles are mentioned in many papers using TCO. Many of these papers are comparing the electric vehicle to competitive technology, others are assessing cost issues/barriers of electric vehicles and there are a few that use TCO to optimise certain parts of the vehicle or define electrification strategy.

3.2 TCO general models

As explained in the section 1.1, TCO accounts for the sum of all costs associated with a product from a purchaser's perspective. Hence, the period analysed at a TCO is less or equal to the total product life cycle (Ellram & Siferd, 1993; Saccani et al., 2017). Whereas the calculation of TCO is present in the purchasing process of companies, the reason to use it may vary. Saccani et al. (2017) identified four different objectives in the literature to apply TCO in the business context: assessment of the economic viability and market acceptance of new technologies; supplier selection; "one-off" purchase; and technical optimisation or dimensioning decisions.

Regardless of the objective, TCO models have in general a common structure. Saccani et al. (2017) propose a comprehensive TCO conceptual model for durable consumer goods (Table 3.2) composed of two dimensions: temporal phases and processes. The former refers to the different stages of product ownership, such as selection and purchase, while the latter refers to activity groups of different types, such as ownership or usage. These activities can be accounted for as *monetary costs*, which generate negative cash flows, or *opportunity costs* (non-monetary costs), which prevent positive cash flows (Saccani et al., 2017).

Moreover, the authors explain a TCO model can be either specific for different types of customers and products or an average of a group of customer types, products or both, leading to the four application modes presented in the Table 3.3.

This proposed categorisation of TCO parts leads to a less overwhelming conceptual

Table 3.2: Dimensions of a TCO conceptual model of durable consumer goods and the events that trigger each phase, adapted from Saccani et al. (2017).

	TEMPORAL PHASES				
PROCESSES	**Selection**	**Deployment**	**Exploitation**	**End of Life**	
Decision-making **Ownership** **Training** **Usage** **Support**	*Need becomes evident*	*Ownership acquisition*	*Start of exploitation*	*End of exploitation*	*End of Ownership*

Table 3.3: Application modes of TCO model, adapted from Saccani et al. (2017).

	CUSTOMER	
PRODUCT	**Specific**	**Average**
Specific	One-to-one TCO	Average Customer TCO
Average	Average Product TCO	Average TCO

model than what previous literature proposed. An extensive (but not exhaustive) list is presented by Ferrin and Plank (2002) and Ellram and Siferd (1993) with more than 310 possible cost drivers and activities and more than 13 categories to perform a TCO analysis. As pointed out by Ellram (1995) and Ellram and Siferd (1998), the complexities of the organisational, measurement and data collection are some of the reasons for limited TCO adoption at the time.

From a conceptual model, Saccani et al. (2017) propose a process to adapt it for a specific durable consumer good being analysed and to reduce its complexity (Figure 3.2). First, define the data requirements and identify the data available. From that, it is possible to understand how customer or product-specific a model can and needs to be. Then, run a pilot test to assess the relevance of each cost aspect. Lastly, remove the irrelevant variables to build a reduced model, adapted for the context and product analysed.

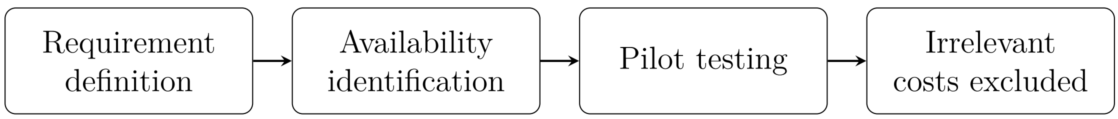

Figure 3.2: Process to reduce TCO model complexity (Saccani et al., 2017).

Besides the identification of the cost aspects and the mode of application for a TCO model in a specific context, the literature also presents different approaches to evaluate the TCO. Ellram (1995) consolidates into three types of models: dollar-based direct cost, dollar-based formula and value-based. The dollar-based models use what Saccani et al. (2017) defined as *monetary costs*. Dollar-based direct costs are TCO models that use cost factors or ratios, and dollar-based formula uses mathematical equations to model costs.

In contrast, value-based models combine both monetary and non-monetary costs. In these cases, weights are used to account for the importance of qualitative criteria. Lizot et al. (2021) provide an application of a value-based approach. The authors combined TCO evaluation of monetary costs with Multi-Criteria Decision Analysis (MCDA) for non-monetary costs to improve cost management in family farming. MCDA is a methodology that evaluates quantitatively an alternative by defining scores and weights for each qualitative criterion (Lizot et al., 2021). However, the methodology is subjective and restricted to the application it was created for(Lizot et al., 2021).

3.3 TCO for battery-electric vehicles

3.3.1 Realistic models

The calculation of TCO for electric vehicles, for both consumer and commercial use, has several particularities, as mentioned in the section 1.1. Besides, depending on the application context, the most representative costs can change (Taefi et al., 2017). Thus, improving the accuracy and comprehensiveness of the calculation has been the goal of many authors.

Delucchi and Lipman (2001) did a pioneer work on TCO modelling for battery-electric vehicles (BEVs). BEVs are any type of vehicle powered by rechargeable batteries, whereas BEHVs are only heavy vehicles, such as trucks. They proposed the division of TCO into three major parts to create an integrated model that can account for initial cost, vehicle performance and life cycle cost (Table 3.4). The first part was a sub-model of vehicle cost and weight considering manufacturing and battery cost. The second part was a sub-model of vehicle energy which simulates all vehicle forces to fulfil the user's requirements. The simulation accounted for energy consumption of individual components, driving style, and heating/cooling systems, considering trip parameters (vehicle speed, acceleration, road grade and trip duration) and vehicle parameters (weight and engine efficiency). As explained by the authors, these first two parts are circular dependant on each other since the vehicle design and weight affects its maximum power, efficiency and cost.

The last part was the periodic ownership and operating costs regarding maintenance, repair and insurance, which depend on the vehicle technology and were deemed as significant as the initial cost in the TCO. To cope with the lack of information on BEV life cycle cost, Delucchi and Lipman (2001) used known data from internal combustion engine (ICE) vehicles to calculate BEV values relative to some dependent variable. For example, they calculated the cost of tire replacement by calculating the tire life relative to vehicle weight change from ICEV to BEV.

Table 3.4: Integrated TCO model used by Delucchi and Lipman (2001).

Vehicle cost and weight	Vehicle energy use	Periodic ownership and operating cost
Battery cost Manufacturing cost	*Trip*: speed, acceleration, road grade, duration *Vehicle*: weight, engine efficiency	Insurance Maintenance Repair

Davis and Figliozzi (2013) also proposed an integrated TCO model, but specific for BEHVs. There are four models: cost minimisation model of vehicle ownership, energy consumption and range model, continuous approximation model for routing constraints, and real-world energy estimation from speed profiles. There are three main aspects explored to improve the TCO modelling.

First, the use of a cost minimisation model is subject to route and energy constraints. Second, the improvement of the continuous approximation model that simplifies a Vehicle Routing Problem (VRP, see section 5.1.1). A VRP is a discrete problem as each node has a specific location in space. On the contrary, a continuous approximation is based on the spatial density of customers. As the number of nodes and the VRP complexity increases, a problem is more related to a continuous function (Davis & Figliozzi, 2013). Lastly, the authors used speed profiles from empirical velocity curves (Motor Vehicle Emission Simulator models) to add real-world driving conditions to the energy consumption estimation. Each of the curves represents the speed at every instant of a type of vehicle in different types of applications.

A different approach was proposed by Ghandriz et al. (2020a) on calculating TCO for BEHVs with and without a driver for autonomous vehicles. Their model focuses on optimising the vehicle propulsion system components in different transportation scenarios. In order to account for the uncertainty of real-world scenarios, the authors modelled four different categories of road hilliness from the literature (i.e., the elevation faced by the vehicle at each kilometre driven on a route), which are not restricted to a determined geographical location: flat, predominantly flat, hilly, and very hilly (Figure 3.3). The different hilliness of the road will lead to different energy requirements of the vehicle (Ghandriz et al., 2020a). Besides, as different types of trucks have different loading/unloading conditions, four schemes were defined to account for the difference in cost and duration in the TCO.

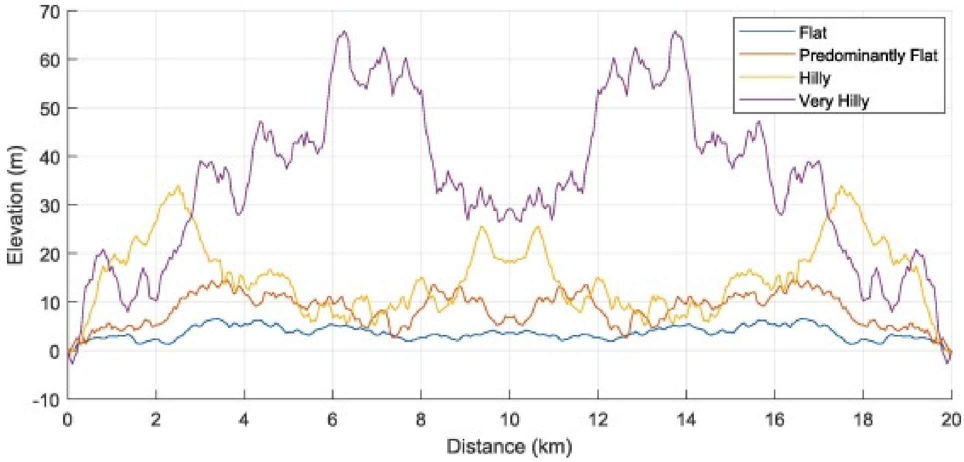

Figure 3.3: Elevation of a back and forth travel for each hilliness category (Ghandriz et al., 2020a).

3.3.2 Cost-based models

Davis and Figliozzi (2013), Delucchi and Lipman (2001), and Ghandriz et al. (2020a) TCO models considers physics and use complex mathematical equations to estimate more realistic values. However, this is not a standard in the literature. Taefi et al. (2017) proposed a cost-based approach for calculating a TCO of a BEHV where the main focus is on having the formulation of costs thorough and the physics part is approximated instead of extensive calculation. The TCO model is divided into one-time investment (X_m), periodic fixed cost (Y_m) and kilometre-dependent cost (Z_m). The division makes it easier to convert the costs to a present value, represented on equation (3.1), where m is the period and d distance travelled (Taefi et al., 2017).

$$TCO = \sum_{m=0}^{M} \frac{X_m}{(1+r)^m} + \sum_{m=1}^{M} \frac{Y_m}{(1+r)^m} + \sum_{m=1}^{M} \sum_{d=1}^{D} \frac{Z_d \cdot d}{(1+r)^m} \tag{3.1}$$

Taefi et al. (2017) did a pioneer work by considering the battery degradation when charging and modelling partial recharging to increase the maximum range for TCO models. To account for the battery degradation, they calculated the impact of decreasing battery state of health (SOH) over time. The SOH is the real maximum battery capacity that reduces over time as the battery degrades. They defined through equation (3.2) a linear relationship with SOH, the total distance travelled R, and the battery warranty K in kilometres. By doing so, they were able to account for the impacts of the battery degradation on the range and cost. The battery end of life of 80% SOH used by the author is a standard measure in the literature and industry (Taefi et al., 2017).

$$SOH = 1 - 0.2 \cdot \frac{R}{K} \tag{3.2}$$

For partial recharging, Taefi et al. (2017) defined the charging range from state of charge (SOC) 10% to 70%. The SOC is the battery level. This is done to take advantage of a linear charging characteristic of a lithium-ion battery that is not present when charging the whole battery capacity. Figure 3.4 from the authors was based on a battery charging curve following the extensively used constant current voltage algorithm (Gao et al., 2019). The time required to charge the defined range of SOC 10% to 70% is roughly one-third of the time needed from SOC 0% to 100% (Marra et al., 2012).

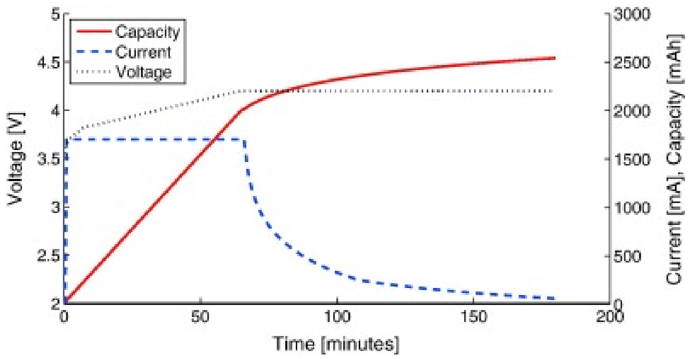

Figure 3.4: Charging curve of an EV lithium-ion battery (Taefi et al., 2017).

Moreover, Taefi et al. (2017) use field test data instead of manufacturers' data in the TCO calculation to get more accurate energy consumption that leads to better estimation of battery-related cost. Lastly, the authors suggest that it is necessary to calculate for each vehicle and context the most cost-efficient planning horizon for the ownership, contrary to the literature than has proposed a minimum or maximum value. That means, instead of fixing the period of use of a vehicle at, for example, six years, it should be analysed if a lower or even greater period should be considered when analysing the TCO.

Similarly, Tanco et al. (2019) considered the battery to be an important parameter and includes the battery end of life (EOL) in the TCO calculations. It is important to monitor when the battery will reach its EOL as a battery replacement affect hugely the TCO of a BEHV. Additionally, Tanco et al. (2019) created a TCO model that can handle different input data from different countries such as tariffs, taxes and electricity prices. The ability of a TCO model to handle different input data makes it possible to analyse the effects policies have on the BEHVs' TCO.

3.3.3 Probabilistic models

The TCO model discussed so far has had deterministic parameters. Wu et al. (2015) proposed a probabilistic simulation model, which Danielis et al. (2018) developed further, that is better able to account for the uncertainty of the TCO model's parameters. In both models, a TCO per km is calculated and the main probabilistic (stochastic) parameters are electricity price (variation over the day and the years), fuel economy/energy consumption (due to traffic variability) and resale value (depreciation variability). Wu et al. (2015) created a statistical distribution for these variables based on secondary data collection. They evaluated the TCO for three different periods of use (2014, '20 and '25), which can give a glimpse of how the TCO might evolve in the future. Moreover, Danielis et al. (2018) brought light to the impact of analysing TCO among different countries, since each country has its own cost structure regarding electricity prices, insurance premiums, and subsidies.

3.4 Energy consumption prediction

The energy consumption prediction is important for the TCO calculation as energy use is a central variable when considering the cost for motor vehicles (Delucchi & Lipman, 2001). Besides, the main drivers to defining technical specifications of BEHVs come from the proper understanding of the operations.

J. Wang et al. (2018) proposed an energy consumption model considering driving behaviour, road topography, weather conditions, and traffic situation. This is done by using an offline and an online (real-time) algorithm. The offline algorithm will take data from three external sources to obtain information about the (1) type of paths to be driven, (2) the road slope, and (3) temperature and wind. The driving behaviour is modelled as three driving speeds (maximum, minimum, nominal) based on the path type information (1). With this initial prediction, the online algorithm updates the model by collecting real-time data from the vehicle to update the driving behaviour data and consider real-time traffic. This information is summarised in

Table 3.5.

Table 3.5: Input variables for the energy consumption model of J. Wang et al. (2018)

Offline algorithm →	**Online algorithm**
Three Driving speeds	Driving behaviour
Road slope	Traffic
Temperature and wind	

Basso et al. (2021) also proposed a more accurate way to predict energy consumption, but instead of an online algorithm, they used empirical data. The authors developed a three steps probabilistic machine learning energy model. They combined map data and the likelihood based on measured data with posterior measurements. Then, this energy model is combined with a two-stage routing model. In the first stage, the energy cost for each link on a network of intersections (such as street corners) is calculated using the energy model and the best path between all nodes (such as customer locations) is found. In the second stage, an electric VRP (EVRP, which considers charging en route) is performed taking into consideration the variance of the energy consumption (stochastic) and traffic conditions from different periods of the day (empirical data).

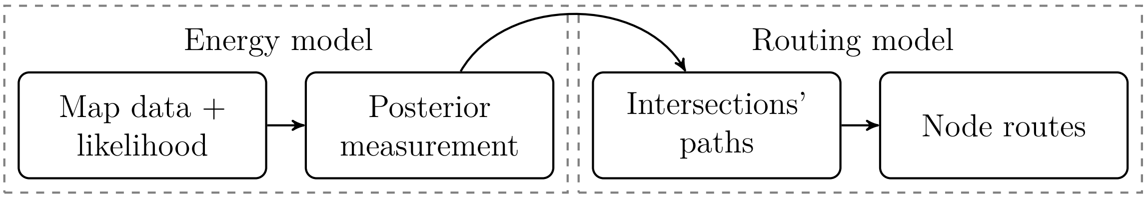

Figure 3.5: Conceptual representation of the model of Basso et al. (2021).

3.5 Supply chain impacts

From a business perspective, the operation of the BEHVs can impact the supply chain differently than most businesses are used to. The diesel truck is the most widely known engine type and is therefore used as a reference point for the BEHV even though those technologies work differently (Sandén & Wallgren, 2017). The BEHV can have lower weight capacity (allowed weight of cargo or payload) due to a heavy battery, and the charging strategy (overnight or daytime) can affect the performance of the truck that may affect the supply chain (Kin et al., 2021).

Lower capacity, increased operation cost and longer transport time might not be ideal in supply chains where time and cost are important. The freight industry is commonly an intermediary in supply chains and is relied on by other supply chain members (Sandén & Wallgren, 2017). Commonly measured key performance indicator (KPI) for a truck in freight operation is utilisation (Kin et al., 2021; Kovács, 2017; Sandén & Wallgren, 2017). Utilisation and previously mentioned factors are likely to be considered before purchase as they are likely to be included in the specifications.

A charging strategy is a decision of which charging station type to use so a vehicle of a certain type can complete the route with its battery capacity (Kin et al., 2021). There are three different types of charging stations commonly used: the depot charging station, which is private and only the owner can use; the public charging station, which is located in public spaces, administrated by the charging point operator, and anyone can use when it is free; and the semi-public charging station, which can be used by anyone but the area is restricted of access (opening hours) or the use is conditional (only for customers) (Lindgren et al., 2021). Semi-public charging stations are usually used in combination with another activity (while loading or unloading, during a break), reducing the overall cost of charging.

Common strategies are overnight charging (only depot charging), opportunistic charging (only public charging), hybrid strategy (combine types), and managed strategy (cost-effective decision). The charging strategy depends on the range and route characteristics, which affects energy consumption, but also the availability of charging stations. If there is a need for a day-time charge, the operation cost will increase due to higher electricity prices on the road and drivers' cost while charging, and transport time might increase due to detours to nearest charging stations (Kin et al., 2021; Pelletier et al., 2016). New charging types and strategies may emerge over time as the market grows and change this view in the future (Lindgren et al., 2021).

From the mentions above, trade-offs for battery sizes are noticeable and are presented in Table 3.6. The reason to choose a smaller battery is that it costs less than a bigger one but the truck will have a shorter range (Danielis et al., 2018; Tanco et al., 2019). Besides, the weight capacity is decreased by a bigger battery which can decrease the utilisation of the cargo space of the vehicle (Kin et al., 2021). In contrast, the charging strategy is not straightforward and depends on range requirements. If the battery chosen has a maximum range that is less than the range requirements, it will require en route charging, which will increase cost (Kin et al., 2021; Pelletier et al., 2016). If the range is higher than the required, then the operator can choose overnight charging, which cost less.

Table 3.6: Trade-offs between battery size when considering supply chain (SC) impact.

SC IMPACT ON	BATTERY SIZE	
	Smaller	**Bigger**
Initial cost	Lower	Higher
Range	Lower	Higher
Weight capacity	Higher	Lower
Charging strategy	Depends on range and route	

3.6 Purchasing process

The supply chain might be considered a stakeholder in the purchasing process. The traditional purchasing process starts with determining functional or technical specifications for the truck by getting input from relevant stakeholders and is followed by the selection of suppliers depending on what they offer (Weele, 2018). Sandén and Wallgren (2017) presents the MEET model that companies can use to evaluate switching to an electric truck and considers operational, supply and investment risks relevant to currently used technology. The supply risk includes many energy suppliers, local availability, raw material availability and infrastructure maturity (Sandén & Wallgren, 2017). If there are high supply risks, the cost will be higher when there are charging en route due to detours and higher electricity prices compared to depot (Kin et al., 2021). Mapping of supply risk may therefore be useful to evaluate the cost of charging en route or the necessary infrastructure investment and can be considered during the purchasing process.

3.7 TCO findings summary

None of the found TCO models for electric vehicles considered cost related to selection and acquisition like the general models (Ellram & Siferd, 1993; Saccani et al., 2017). The deployment and exploitation are covered in all TCO models found but differently across the authors. Davis and Figliozzi (2013), Delucchi and Lipman (2001), and Ghandriz et al. (2020a) use complex and more realistic calculation to estimate energy cost while Danielis et al. (2018), Tanco et al. (2019), and Wu et al. (2015) simplified the energy calculations with estimations.

The handling of cost regarding *End of life* in TCO models for electric vehicles was often assumed to be a certain value based on the year and/or mileage and subtracted from the sales value (Danielis et al., 2018; Davis & Figliozzi, 2013; Taefi et al., 2017; Tanco et al., 2019; Wu et al., 2015).

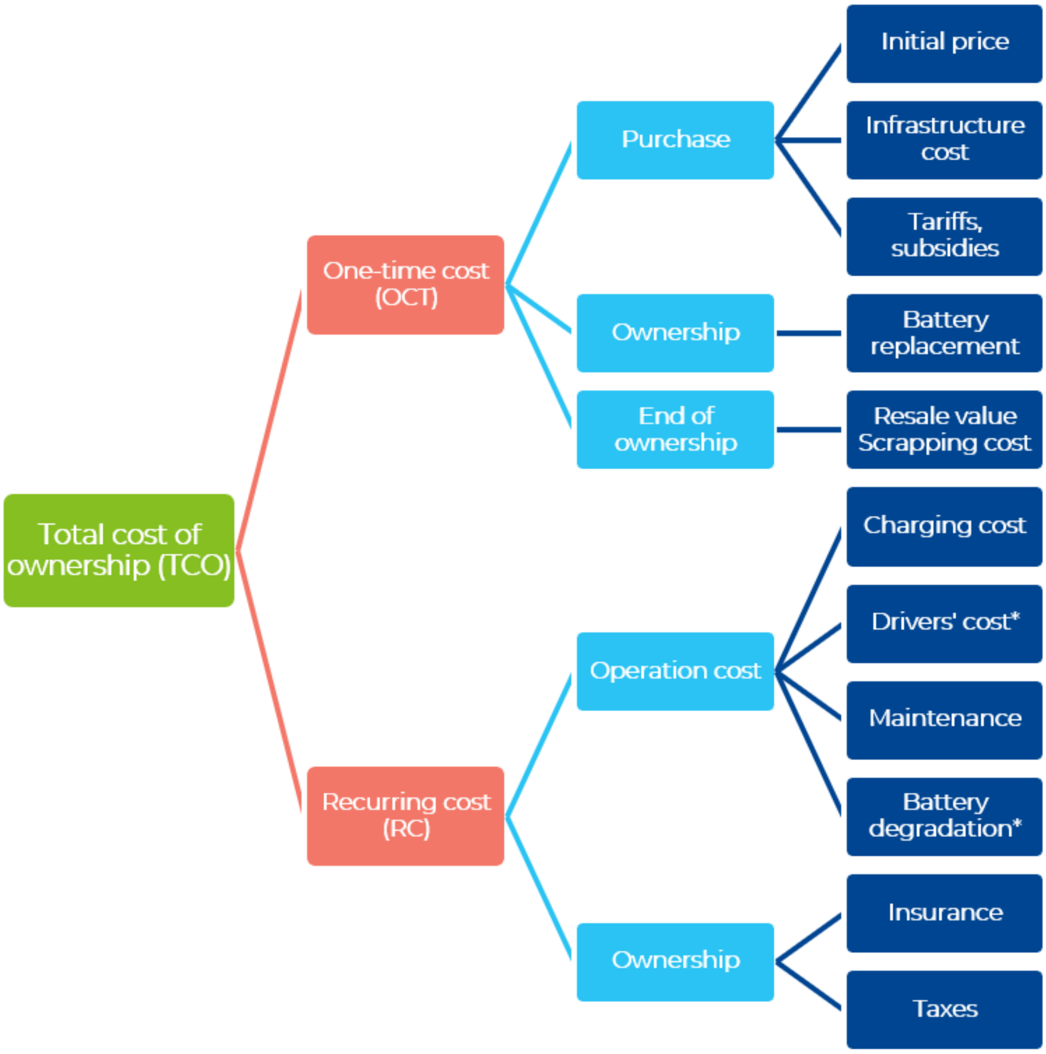

Figure 3.6: An adaption of the TCO framework presented in numerous studies (Danielis et al., 2018; Taefi et al., 2017; Tanco et al., 2019; Wu et al., 2015).

The frameworks for TCO presented in the above papers could be consolidated as shown in Figure 3.6. The TCO is divided into one-time-cost (OTC) and recurring cost (RC), which is similar to how van Velzen et al. (2019) did in his literature study. This division makes it straightforward to discount the costs to a present value. Taefi et al. (2017) divided the TCO into one-time investment cost, fixed periodic investment and kilometre depending on the cost which is similar to OTC and RC. Further division of OTC and RC into TCO processes (see Table 3.2) was evident in Danielis et al. (2018) and Tanco et al. (2019) but would be rather easy to include in other frameworks. The costs used in the TCO frameworks, except for drivers' costs and battery degradation (marked with *), are common in numerous papers. Drivers' costs are only considered by Davis and Figliozzi (2013) and Ghandriz et al. (2020a) where they are assessing TCO in freight transport, which becomes irrelevant when analysing private electric vehicles as in Danielis et al. (2018) and Wu et al. (2015). Only Ghandriz et al. (2020a) and Taefi et al. (2017) calculated the battery degradation and discount the battery continuously through the ownership period, whereas other papers seem to simply discount the whole vehicle where the battery is included.

4

Model conceptualisation

In this chapter, the use of TCO models is understood within the business context of Volvo and the broad market. By combining the data collected from the business and market context with the information acquired from the literature review, the conceptual TCO model is proposed.

4.1 Business context

Volvo already offers services for planning and structuring a BEHV fleet. However, there is a growing interest in relating this planning with cost aspects to measure the impact of any decision related to BEHV such as route planning, charging strategy, and vehicle design. Besides, by converting complex decisions into a total cost of ownership value, the company has a common language when interacting with customers.

Following Saccani et al. (2017)'s definition in Table 3.3, the TCO model had to be product and customer-specific (One-to-one TCO). Nonetheless, the TCO model would need to be flexible enough that with small changes, it would be able to handle a large variety of clients (such as urban distribution, regional distribution, long-haul distribution, refuse collection) and locations (Europe and the USA). Moreover, the model would be able to provide recommendations not only for customers that have detailed information about their operation but also for customers that have only rough numbers. Lastly, Volvo already has tools for energy prediction, and it was desired to integrate them into the TCO model.

As Volvo did not have experience in using a TCO optimisation model, it was required that comparative commercial solutions were analysed (section 4.2). So the TCO model would be competitive with what competitors or companies specialised in electrification are offering.

4.2 Market context

Electric vehicles (EVs) can be considered a radical innovation due to their high uncertainty and ambiguity, which are a huge barrier to the adoption of a technology (Sierzchula, 2014). The technology is also complex, very different from the currently most widely used technology (ICEV), and a lot of information is required to make a cost-effective decision. However, due to bounded rationality and low experience with EVs, the wiliness to adopt it decreases (Dyerson & Pilkington, 2005; Sierzchula, 2014). That said, fleet and operation managers are not used to electromobility, investment in infrastructure, and precise planning for routes and charging of each vehicle. Thus, there is a clear pain point that many companies are trying to cover.

The market for comparable solutions is composed of young small software companies (such as eIQ, Panion, and inno2fleet), known software companies that were already in the logistics and operation market and improved their solution to include electromobility (such as Geotab, route4me, WEBFLEET), utility or energy companies that create a solution for electromobility (Duke Energy), and OEMs which have developed internally (Volvo) or acquired companies from the first category to provide the service like Ford did with the purchase of Electrify (Naughton, 2021).

These companies have built a large database of service providers, vehicle information, charging stations location and incentives. The policies and subsidies for BEVs vary between states in a country and fluctuate, which makes it hard for fleet managers to keep track of all subsidies and their exact amount/percentage (Breetz & Salon, 2018). By adding the customer data and requirements, these companies can offer a platform that is able to assist in different steps of electromobility adoption.

There are solutions for the purchase process that assist in identifying which specific vehicle or route is worth electrifying based on cost savings and sustainability measures compared to the current fleet (mainly composed of ICEVs) (eIQ Mobility, 2020). Some solutions assist in determining and managing the implementation and use of the charging infrastructure (eIQ Mobility, 2020) and to manage the daily operation of the BEV fleet (Electrifi, 2021b). Lastly, some solutions provide everything combined, from adoption to daily use (Electrifi, 2021a). As it is such an important need for the market, some organisations and institutions invested in research and developed tools that are open for anyone to use as NACFE (NACFE, 2018) and Electrification Coalition (Electrification Coalition, 2021) to assist in this manner. The commercial solutions have common inputs and outputs. A summary of this list is presented in Table 4.1.

Table 4.1: Common inputs and outputs in commercially available tools for electrification.

Input	**Output**
Average yearly/daily km	If and what is worth to electrify
Fleet size	TCO comparison (BEV vs. ICEV)
Long list of truck types	Cost savings for charging management
Arrival & departure from depot	CO_2 savings
Lifetime of the vehicle	Comparison of un- and managed charging
Fuel/energy consumption	
Electricity and fuel price	
Maintenance cost per km/year	
Discount rate	
Infrastructure cost by type	
Incentives or subsidies	

The benefit of the analysis of the commercial tools was that it helped validate that the input and output of the TCO model to be developed were in line with what the market wanted. The scope of this work assumes that the customer already has decided to buy a BEHV. Hence, CO_2 savings and TCO comparison (BEHV vs. ICEV) are irrelevant to the model for now. The other inputs and outputs in the Table 4.1 are in line with what was already found in the literature review (see chapter 3).

4.3 Conceptual model

The conceptual TCO model was based on the literature review and the commercial solutions researched and, at the same time, it was made in line with Volvo's business context. The purpose of the model is to support "dimensioning decision", which is supported by Saccani et al. (2017). Although the literature found discussed and defined the TCO from the purchaser's perspective, original equipment manufacturers (OEMs) have an interest in using it (section 4.2). The use of TCO provides a direction, highlights profitability improvements, and support in negotiation (Ellram, 1995), which should also benefit the OEMs.

Largely based upon the TCO framework (Figure 3.6), a conceptual TCO model was made (Figure 4.1). It has four main parts: initial cost, operation cost, ownership cost and end-of-life cost. This subdivision of the TCO model was a combination of the processes and temporal phases of Saccani et al. (2017). The *initial cost* encompasses the ownership acquisition moment, the *operation* and *ownership cost* encompass the exploitation phase, and the *end-of-life cost* set the end of the vehicle ownership. The time from the ownership acquisition until the end of the vehicle ownership period is defined as the planning horizon (or total number of periods). The exploitation phase was divided into the costs of usage of the vehicle (operation cost) and the costs of ownership and support (ownership cost). Within each of these subdivisions, the main defined costs were based on the BEV TCO models.

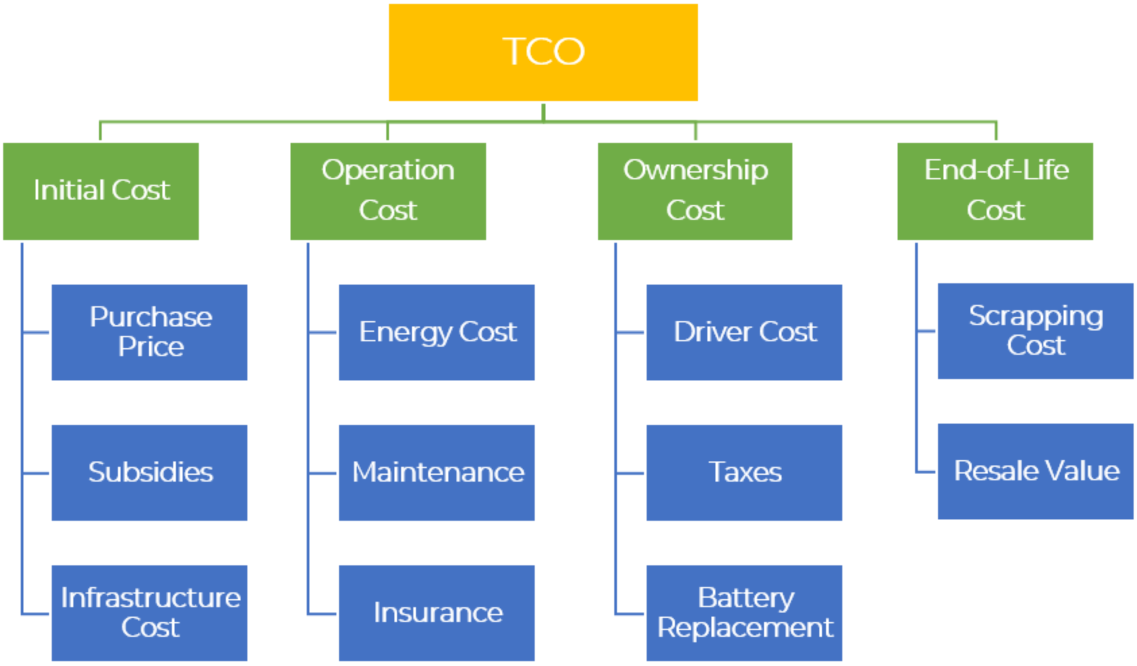

Figure 4.1: Proposed conceptual TCO model.

4.3.1 Initial cost

Initial cost consists of the purchase price, tariffs & subsidies, and then infrastructure cost. The purchase price was based on the manufacturer's suggested retail price, but it is worth mentioning that the manufacturer's suggested retail price is normally only a starting point for sales price as it depends on various factors such as location in a country (Danielis et al., 2018). The purchase price was dependent on vehicle specifications such as battery size, truck class and truckload capacity, which is similar to what Tanco et al. (2019) did. Even though commercially there are various payment methods available for vehicle purchasing, a single payment was chosen, as done by numerous papers (Davis & Figliozzi, 2013; Taefi et al., 2017; Tanco et al., 2019).

Tariffs and subsidies can change the final purchase price. Tariffs vary between countries and are added to the purchase price (Tanco et al., 2019). Subsidies, if available for a vehicle class, can lower the purchase price but they are also country dependent (Danielis et al., 2018; Davis & Figliozzi, 2013; Taefi et al., 2017).

It is assumed in the conceptual model that investment in charging infrastructure is needed for every individual BEHV added to the fleet, which was similarly done by Ghandriz et al. (2020a). The cost of charging infrastructure depends on the required charging power for each BEHV (Tanco et al., 2019).

4.3.2 Operation cost

Operation cost consists of energy cost (or charging cost) and maintenance cost. Energy is a central variable for operation as it will affect both the range of the vehicle and energy cost (Delucchi & Lipman, 2001). The energy cost is made of energy used during the operation and the electricity price at each place the vehicle is charged (such as depot or public charging stations) (Danielis et al., 2018; van Velzen et al., 2019). Electricity prices at the depot are usually lower than electricity prices at the charging station en route (Kin et al., 2021).

The maintenance and insurance cost are classified as an operational cost, similar to Ghandriz et al. (2020a). Maintenance consists of regular maintenance and tyres. As maintenance (Taefi et al., 2017) and insurance (Maibach et al., 2006) usually increases with usage, both costs were kilometre dependent.

Unlike the TCO framework (Figure 3.6), battery degradation was excluded from the conceptual model. The linear battery degradation function used by Taefi et al. (2017) is far from reality, as lots of factors can affect the battery, such as charging behaviour (Barré et al., 2013; Hannan et al., 2017). Besides, limited research is available on cost due to battery degradation. Hence, a battery degradation model would add uncertainty to the model results.

4.3.3 Ownership cost

Ownership cost consists of driver cost, taxes and battery replacement cost. The driver is considered a full-time employee with a monthly salary. Driver cost was found to be a significant cost for truck operation as a driver is always needed for truck operation unless it is autonomous (Davis & Figliozzi, 2013; Ghandriz et al., 2020a), considerably increasing the cost of an extra vehicle.

Battery replacement is discussed by Tanco et al. (2019), where it was calculated that the battery replacement was very unlikely to occur during a 10-year lifetime while Taefi et al. (2017) considered a battery replacement was required as soon as the warranty expired. Following Tanco et al. (2019), the conceptual model included the battery replacement, but no battery replacements are expected to happen during the ownership period, which is limited by the daily mileage.

4.3.4 End-of-life cost

End-of-life cost consists of resale value and scrapping cost. There is a lot of uncertainty about what the resale value of the BEHV is, if any, at the end of the ownership period and in some cases, there might be a scrapping cost (Davis & Figliozzi, 2013; Taefi et al., 2017). However, the literature agrees on using depreciation as a reference for estimating the terminal value. Thus, the difference between the scrapping cost and the resale value is defined by the vehicle depreciation rate that depends on its use (total kilometres) and length of ownership.

5

Model analytical formulation

In this chapter, TCO analytical model is described. First, the theoretical background related to VRP and ACO used for the models' formulation is presented. Second, the complete model formulation is presented and explained. Lastly, the alternative models derived from the complete model are presented and explained.

5.1 Model's theoretical background

Vehicle Routing Problems are the main part of all models proposed in this chapter, thus a brief introduction to the concept is presented. As the routing problem size grows, it becomes harder to find optimal solutions. Hence, Ant Colony Optimization was selected to deal with these cases, and it is also briefly presented.

5.1.1 Vehicle Routing Problems

A Vehicle Routing Problem (VRP) is similar to the Travelling Salesman Problem (TSP). A TSP is a task of choosing the shortest (lowest cost) route to go through all required nodes (Flood, 1956). However, on a VRP, due to some constraints (such as capacity or time), a single vehicle is only able to visit a subset of all nodes, requiring more than one vehicle to complete the task (Dantzig & Ramser, 1959). Figure 5.1 compares the solution of a TSP and a VRP where only a single route is created with the TSP solution while the VRP solution creates three routes from a single origin.

VRP is the general term for a vast possibility of problems. The VRP literature can be classified by the type of study (e.g., exact methods, heuristics), scenario characteristics (e.g., number of stops, customer demand), physical characteristics (network design, type of vehicles), and the characteristics of the information and data used (Braekers et al., 2016).

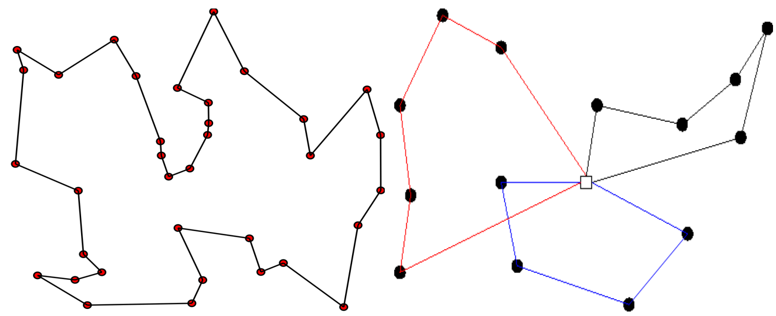

Figure 5.1: Graphic representation of a TSP (left) and a VRP (right) solution.

The classical VRP is the Capacitated VRP (CVRP) in which the vehicles are identical, they have limited load capacity, and there is only one depot that is the starting and ending node for all vehicles (Braekers et al., 2016). From it, depending on the scenario and physical characteristics, the problem can be expanded. For example, when each node has a specific period of the day they must be visited, this is known as the VRP with Time Windows (VRPTW) (Braekers et al., 2016). If the vehicles are different from each other, it is defined as Heterogeneous fleet VRP (HVRP) (Braekers et al., 2016). For BEVs, there is the need to consider charging stations, battery capacity, battery level and charging amount. This problem is classified as the Electric VRP (EVRP) (Schneider et al., 2014). Each VRP can be combined as needed into a more comprehensive model as illustrated in Figure 5.2.

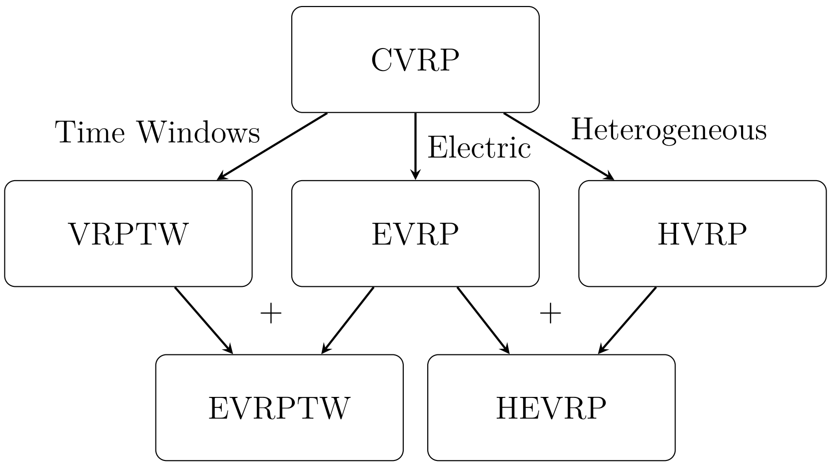

Figure 5.2: Example of VRP sub-problems and their combination.

Some of the VRP classifications are easily implemented with small changes. However, there are more complex problems that require major changes on the problem. For example, the VRP with Lunch Break (VRPLB) optimise the moment and location the driver should have a pause required by law. However, its full implementation almost doubles the problem size (Coelho et al., 2016). Hence, even very small problems take a lot of time to solve. When that happens with any VRP type, the literature usually creates simplification or heuristic models to find close to optimal solutions.

5.1.2 Ant Colony Optimization

Ant Colony Optimization (ACO) is a meta-heuristic and a common term for different versions of ant system algorithms (Dorigo & Di Caro, 1999). A heuristic is a cognitive tool used to make fast decisions under uncertainty, which is based on "discovery" and "investigation" (Neth & Gigerenzer, 2015). In computer science, heuristics are used to obtain near optimal solutions in a reasonable time, but it does not assure a feasible or optimal solution (Beheshti & Shamsuddin, 2013). Meta-heuristic is an iterative process that strategically guides heuristics to generate better and more efficient solutions (Beheshti & Shamsuddin, 2013). Whereas ant system algorithms are based on the observed behaviour of real ants in coordinating and structuring their movement (between a food source and the nest, for example) (Colorni et al., 1991).

Ants use a simple communication method through the release of pheromones as they move (Tang et al., 2019). When an ant finds food, for example, on its way back, it will release a pheromone that will guide other ants to the food and back to the nest. As the pheromone evaporates constantly over time, the shorter paths will have a higher concentration of pheromone than longer paths. As a result, other ants will follow shorter paths with higher chances than longer ones, leading over time to a dominant path. Figure 5.3 represents this behaviour: (a) ants discover different paths; (b) pheromone accumulates faster on the shorter path; and (c) ants converge to the shortest path found (Tang et al., 2019).

ACO has been widely used for TSP and VRP with success as it has advantages over other optimisation methods (X. Wang et al., 2016). However, the efficacy of an ACO highly depends on its implementation, since it can easily reach stagnation on a local optimal (Mavrovouniotis et al., 2019). Therefore, a variety of ant system algorithms that have been developed for different VRP types can be found in the literature.

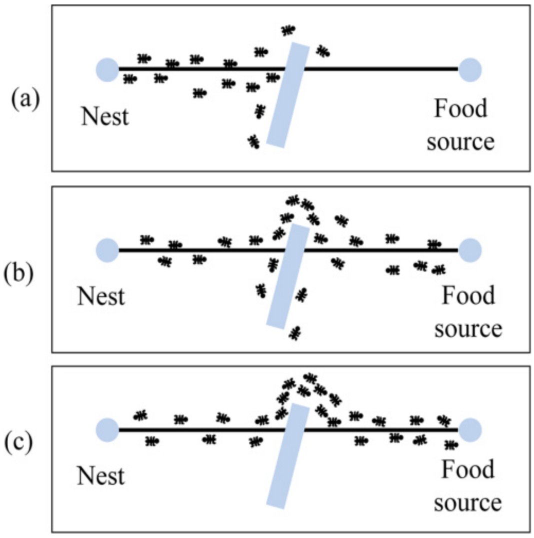

Figure 5.3: Ant foraging behaviour (Tang et al., 2019).

5.2 TCO complete model formulation

Following the definition presented in the section 5.1.1, the model is a VRP with capacity, volume and time windows constraints, energy consumption, and charging within route when required. Besides, it considers a fleet mix, i.e., the vehicles can be different from each other. Hence, the model can be defined as a HEVRPTW: heterogeneous electric vehicle routing problem with time windows. The driver's break is also modelled, but through a simplification, thus it cannot be considered a VRPLB (Coelho et al., 2016). Regarding charging strategies, there is the possibility of overnight charging, opportunistic charging at public or semi-public (at customers and break locations) charging stations, and a hybrid strategy that is a mix of both.

The TCO is composed of the main costs for electric trucks as discussed in the conceptual model (section 4.3). Time is in $[s]$, distances are in $[m]$, weight in $[kg]$, volume in $[dm^3]$, energy is in $[Wh]$, power is in $[W]$, and costs are in $[SEK]$ and are discounted monthly. All sets, parameters and variables of the model are compiled in Table 5.1.

$\mathcal{C}$ is the set of c customers without semi-public charging stations. $\mathcal{G}$ is the set of g customers with semi-public charging stations. $\mathcal{F}$ is the set of f public charging stations and $\mathcal{F}'$ is the set of charging stations and their D dummies, such that $\mathcal{F}' = \mathcal{F}$ when $D = 1$. $\mathcal{H}$ is the set of h lunch break locations that may or may not have (semi-)public charging stations. $\mathcal{N}$ is the set of nodes. $\mathcal{N}_0$ is the set of nodes without the depot (node 0). $\mathcal{V}$ is the set of v heterogeneous trucks. If a truck is allowed to be used more than once, it should be duplicated in the input.

The input parameters for the routing are nodes coordinates for route visualisation, the demand weight λ_i of node i, the demand volume ϕ_i of node i, the vehicle curb weight W^v, the weight capacity Λ^v for each truck variant v, the volume capacity Φ^v for each truck variant v, the lower bound time windows L_i and the upper bound time windows U_i for node i, the service time S_i of customer i, the distance D_{ij} between nodes i and j, the travel time T_{ij} between nodes i and j, and the driving time limit by law L_d allowed without a break. For the linearised routing constraints that requires a sufficiently large constant is required, $M = max\{U_i + T_{ij} + S_i - L_i\}$ is used.

The input parameters for the energy are the energy coefficients α_{ij} and β_{ij} between nodes i and j, the battery utilisation γ, the net battery capacity B^v for each truck variant v (which is the total battery capacity multiplied by γ), the charging rate R_i of public and semi-public charging station i ($R_i = 0$, if i has none), and the vehicle's system power S_e. For the linearised energy constraints that requires a sufficiently large constant, $B_{max} = max_v B^v$ is used.

The input parameters for the costs are planning horizon P, the monthly discount rate D_r, the number of working days per month W_d, the vehicle acquisition price A^v for each truck variant v, the subsidies for vehicle acquisition and charging infrastructure S_t, the charging infrastructure cost I_f, the electricity price at the depot E_d, the surplus electricity price to charge en route E_x, the monthly driver's salary D_s, the vehicle maintenance cost per kilometre M_t, the taxes per vehicle T_x, and the insurance cost per vehicle I_s. The binary parameter R_b^p has a value of 1 if the battery of all vehicles has to be replaced during its ownership at period p and B_c is the equivalent battery cost. The parameter D_p is the depreciation rate of the vehicles over the ownership period.

The decision variables present in the model are: the binary variable x_{ij} has a value of 1 if the arc from node i to node j is in the optimal route; the binary variable z_{ij}^v has a value of 1 if the arc from node i to node j uses truck variant v; w_{ij} is defined as the vehicle load weight from node i to node j; s_i is the serving duration at node i; y_i is the arrival time at node i; τ_i is the arrival time back to the depot with i as the final node before the depot; e_{ij} is the arc energy cost from node i to node j is in the optimal route; b_i is the current battery level at node i; δ_i is the charging amount at public and semi-public charging station i; the binary variable μ^v has a value of 1 if the truck variant v has to stop at a lunch break location.

The optimisation objective is to minimise the total cost of ownership:

$$Minimise \sum_{v\in\mathcal{V}}\sum_{j\in\mathcal{N}}(A^v + I_f - S_t)z_{0j}^v \tag{5.1}$$

$$+ \sum_{p}^{P} \frac{(\sum_{(i,j)\in\mathcal{N}} E_d e_{ij} + \sum_{i\in\mathcal{F}'} E_x \delta_i + (M_t + I_s)\sum_{(i,j)\in\mathcal{N}} D_{ij}x_{ij})W_d}{(1+D_r)^p} \tag{5.2}$$

$$+ \sum_{p}^{P} \frac{(D_s + T_x + R_b^p B_c)\sum_{j\in\mathcal{N}} x_{0j}}{(1+D_r)^p} \tag{5.3}$$

$$- \frac{(1-D_p)\sum_{v\in\mathcal{V}}\sum_{j\in\mathcal{N}} A^v z_{0j}^v}{(1+D_r)^P} \tag{5.4}$$

subject to:

$$\sum_{i\in\mathcal{N}} x_{ij} = 1 \qquad \forall j \in \mathcal{C}\cup\mathcal{G} \tag{5.5}$$

$$\sum_{i\in\mathcal{N}} x_{ij} \leq 1 \qquad \forall j \in \mathcal{F}'\cup\mathcal{H} \tag{5.6}$$

$$\sum_{j\in\mathcal{N}} z_{ij}^v - \sum_{j\in\mathcal{N}} z_{ji}^v = 0 \qquad \forall i \in \mathcal{N}_0, v\in\mathcal{V} \tag{5.7}$$

$$\sum_{v\in\mathcal{V}} z_{ij}^v = x_{ij} \qquad \forall (i,j) \in \mathcal{N} \tag{5.8}$$

$$\sum_{j\in\mathcal{N}_0} z_{0j}^v \leq 1 \qquad \forall v \in \mathcal{V} \tag{5.9}$$

$$s_i = S_i \qquad \forall i \in \mathcal{C}\cup\mathcal{G}\cup\mathcal{H} \tag{5.10}$$

$$s_i = 3600\cdot\delta_i/R_i \qquad \forall i \in \mathcal{F}' \tag{5.11}$$

$$y_j \geq y_i + T_{ij} + s_i - M(1-x_{ij}) \qquad \forall i\in\mathcal{N}, j\in\mathcal{N}_0 \tag{5.12}$$

$$L_i \leq y_i \leq U_i \qquad \forall i\in\mathcal{N} \tag{5.13}$$

$$\tau_i \geq y_i + T_{i0} + s_i - M(1-x_{i0}) \qquad \forall i\in\mathcal{N}_0 \tag{5.14}$$

$$L_0 x_{i0} \leq \tau_i \leq U_0 x_{i0} \qquad \forall i\in\mathcal{N} \tag{5.15}$$

$$\sum_{j\in\mathcal{N}} w_{ji} - \sum_{j\in\mathcal{N}} w_{ij} = \lambda_i \qquad \forall i \in \mathcal{N}_0 \quad (5.16)$$

$$\lambda_j x_{ij} \leq w_{ij} \leq \sum_{v\in\mathcal{V}} (\Lambda^v - \lambda_i) z_{ij}^v \qquad \forall i \in \mathcal{N}_0 \quad (5.17)$$

$$\sum_{(i,j)\in\mathcal{N}} \phi_i z_{ij}^v \leq \Phi^v \qquad \forall v \in \mathcal{V} \quad (5.18)$$

$$e_{ij} \geq \alpha_{ij}(\sum_{v\in\mathcal{V}} W^v z_{ij}^v + w_{ij}) + \beta_{ij} x_{ij} + S_e(y_j - y_i) - B_{max}(1 - x_{ij}) \quad \forall i \in \mathcal{N}, j \in \mathcal{N}_0 \quad (5.19)$$

$$e_{i0} \geq \alpha_{i0}(\sum_{v\in\mathcal{V}} W^v z_{i0}^v + w_{i0}) + \beta_{i0} x_{i0} + S_e(\tau_i - y_i) - B_{max}(1 - x_{i0}) \qquad \forall i \in \mathcal{N}_0 \quad (5.20)$$

$$b_j \leq \sum_{v\in\mathcal{V}} B^v z_{0j}^v - e_{0j} + B_{max}(1 - x_{0j}) \qquad \forall j \in \mathcal{N}_0 \quad (5.21)$$

$$b_j \geq \sum_{v\in\mathcal{V}} B^v z_{0j}^v - e_{0j} - B_{max}(1 - x_{0j}) \qquad \forall j \in \mathcal{N}_0 \quad (5.22)$$

$$b_j \leq b_i - e_{ij} + B_{max}(1 - x_{ij}) \qquad \forall i \in \mathcal{C}, j \in \mathcal{N}_0 \quad (5.23)$$

$$b_j \geq b_i - e_{ij} - B_{max}(1 - x_{ij}) \qquad \forall i \in \mathcal{C}, j \in \mathcal{N}_0 \quad (5.24)$$

$$b_i \geq e_{i0} \qquad \forall i \in \mathcal{N}_0 \quad (5.25)$$

$$b_j \leq b_i + \delta_i - e_{ij} + B_{max}(1 - x_{ij}) \qquad \forall i \in \mathcal{G} \cup \mathcal{F}' \cup \mathcal{H}, j \in \mathcal{N}_0 \quad (5.26)$$

$$b_j \geq b_i + \delta_i - e_{ij} - B_{max}(1 - x_{ij}) \qquad \forall i \in \mathcal{G} \cup \mathcal{F}' \cup \mathcal{H}, j \in \mathcal{N}_0 \quad (5.27)$$

$$\delta_i \leq \sum_{v\in\mathcal{V}} \sum_{j\in\mathcal{N}} B^v z_{ij}^v - b_i \qquad \forall i \in \mathcal{G} \cup \mathcal{F}' \cup \mathcal{H} \quad (5.28)$$

$$\delta_i \leq S_i R_i / 3600 \qquad \forall i \in \mathcal{G} \cup \mathcal{H} \quad (5.29)$$

$$M\mu^v \geq \sum_{i\in\mathcal{N}\prime} \tau_i^v - L_d \geq -M(1 - \mu^v) \qquad \forall v \in \mathcal{V} \quad (5.30)$$

$$\sum_{i\in\mathcal{N}} \sum_{j\in\mathcal{H}} z_{ij}^v = \mu^v \qquad \forall v \in \mathcal{V} \quad (5.31)$$

$$x_{ij}, z_{ij}^v, \mu^v \in \{0, 1\} \qquad \forall (i,j) \in \mathcal{N}, v \in \mathcal{V}, i \neq j \quad (5.32)$$

Table 5.1: TCO model sets, parameters, and variables.

Sets	
$\mathcal{C} = \{1, ..., c\}$	Set of customers without charging stations
$\mathcal{G} = \{c+1, ..., c+g\}$	Set of customers with charging stations
$\mathcal{F}' = \{c+g+1, ..., c+g+D \cdot f\}$	Set of charging stations and their dummies
$\mathcal{H} = \{c+g+D \cdot f+1, ..., c+g+D \cdot f+h\}$	Set of lunch break locations
$\mathcal{N} = \{0\} \cup C \cup G \cup F' \cup H$	Set of nodes
$\mathcal{N}_0 = C \cup G \cup F' \cup H$	Set of nodes without the depot
$\mathcal{V} = \{1, ..., v\}$	Set of truck variants
Parameters	
c	Number of customers without charging stations
g	Number of customers with charging stations
f	Number of charging stations
D	Multiplier for dummy charging stations
h	Number of lunch break locations
v	Number of truck variants
λ_i	Demand weight [kg] of node i
ϕ_i	Demand volume [dm^3] of node i
W^v	Vehicle curb weight [kg] of truck variant v
Λ^v	Vehicle weight [kg] capacity of truck variant v
Φ^v	Vehicle volume [dm^3] capacity of truck variant v
$[L_i, U_i]$	Time windows [s] of node i
S_i	Service duration [s] at customer i
D_{ij}	Distance [m] between nodes i and j
T_{ij}	Travel time [s] between nodes i and j
L_d	Limit driving time [s] without a break
M	Sufficiently large constant
α_{ij}, β_{ij}	Energy coefficients [Wh/kg,Wh] between i and j
B^v	Net battery capacity [Wh] of truck variant v
R_i	Charging rate [W] of charging station i
S_e	Vehicle's system power [W]
B_{max}	Sufficiently large constant
P	Planning horizon length in months

Table 5.1 – continued from previous page

D_r	Monthly discount rate
W_d	Working days per month
A^v	Vehicle acquisition cost [SEK]
S_t	Total subsidies [SEK]
I_f	Charging infrastructure cost [SEK]
E_d	Electricity price [SEK/Wh] at the depot
E_x	Surplus electricity price [SEK/Wh] charging en route
D_s	Driver cost [SEK/month]
M_t	Maintenance cost [SEK/km]
T_x	Vehicle's taxes [SEK/month]
I_s	Vehicle's insurance cost [SEK/km]
R_b^p	Binary, indicates if battery replaced on period p
B_c	Battery cost [SEK]
D_p	Depreciation rate
Variables	
x_{ij}	Binary, indicates if arc (i, j) is used
z_{ij}^v	Binary, indicates if arc (i, j) is used by truck v
w_{ij}	Vehicle load weight on arc (i, j)
s_i	Service duration at node i
y_i	Arrival time at node i
τ_i	Arrival time at depot with last route node i
e_{ij}	Energy consumption on arc (i, j)
b_i	Battery level at node i
δ_i	Charging amount at charging station i
μ^v	Binary, indicates if truck v visit break location

The objective function is composed of the four parts of the conceptual model: (5.1) is the initial cost, (5.2) is the operation cost, (5.3) is the ownership cost, and (5.4) is the end-of-life cost. The formulation of this objective function was based on equation (3.1) from Taefi et al. (2017). (5.1) and (5.4) are one-time cost from period 0 and the final period, respectively, (5.2) are variable-dependent cost and (5.3) are periodic fixed cost.

Constraint (5.5) ensures that every customer is visited only once. Constraint (5.6) states that each charging station can be visited at most once. If charging stations can be visited more than once, the dummy nodes D should be defined accordingly. This approach increases the number of nodes, but it avoids adding an extra dimension to many variables (Basso et al., 2021). As the charging stations and their dummy equivalent are in the same location, the distance or travel time between them should be set to a large value to restrict these paths. Constraint (5.7) ensures that every vehicle leaves the node it enters, so the same truck variant is used for the whole route of that vehicle. Constraint (5.8) ensures that x_{ij} and z_{ij}^v define the same route. Constraint (5.9) limits each variant to a single vehicle. Constraints (5.10) and (5.11) calculate the service duration for customers, lunch break, and charging stations, respectively. The "service duration" of the lunch break is the length defined by law for a driver's break. Constraints (5.12) and (5.14) calculates the arrival time at the nodes. Constraints (5.13) and (5.15) restrict the arrival time to the time windows of each node. Constraints (5.16) and (5.17) calculates the load of the truck on each arc i to j. Constraint (5.18) defines the volume constraint of the trucks.

Constraints (5.19) and (5.20) calculates the energy cost of the arc i to j. Constraints (5.21)–(5.24) calculates the battery level based on the selected battery capacity. Constraint (5.25) limits the battery level to the required energy to go back to the depot. Constraints (5.26)–(5.28) calculates the required charge at any charging station and the consequently battery level. Constraint (5.29) limits the charging amount at semi-public charging stations and lunch break locations to their respective service duration. Constraints (5.30) and (5.31) indicates if truck variant has to have a break when the total time driving is above the limited defined by law, limiting it to a single stop. Finally, constraint (5.32) defines the three integer variables.

The constraints' formulation is a combination of a few authors. The basic formulation of a VRPTW (5.5), (5.12), (5.13) and (5.16)–(5.18) was based on Desrochers et al. (1988). The energy consumption and charging modelling (5.6), (5.10), (5.11) and (5.19)–(5.28) was based on Basso et al. (2021) and Ma et al. (2021). Finally, the implementation of the truck variant dimension (5.7), (5.8), (5.17)–(5.22), (5.25) and (5.28) was inspired by Bektaş and Laporte (2011) and Golden et al. (1984). The lunch break constraints (5.30) and (5.31) were created to take advantage of the time windows constraints, without the need to fully implement a VRPLB.

The total time τ_i and the arc energy cost e_{ij} calculations are originally non-linear:

$$\tau_i = (y_i + T_{i0} + s_i)x_{i0} \tag{5.33}$$

$$e_{ij} = \alpha_{ij}(\sum_{v \in \mathcal{V}} W^v z_{ij}^v + w_{ij}) + \beta_{ij} x_{ij} + S_e(y_j - y_i) x_{ij} \tag{5.34}$$

Constraints (5.14), (5.19) and (5.20) are the linearisation of equations (5.33) and (5.34), which were based on Bektaş and Laporte (2011) and Cordeau et al. (2007).

5.3 Alternative models

The HEVRPTW is NP-hard, i.e., its computational effort and complexity make it extremely difficult to find the optimal solution through exact methods. This is already true for considerably small cases (20 nodes in total). As it is common to face problems larger than this, three alternative methods are proposed derived from the complete model (section 5.2). All alternative methods still follow the same TCO conceptual model presented in the section 4.3 and are inspired by the complete model formulation (5.2).

5.3.1 Simplified model

This model is a modularisation of the complete model, thus any information explained regarding the latter, also applies to the former. The complete model can be divided into three main parts: the public charging, the heterogeneous fleet and the lunch break. Removing any of these parts can drastically reduce the computational time. However, this requires experimentation with the problem being analysed to understand the problem.

For example, one could start by solving the problem without these three parts. That means, there is no option to charge on public charging stations, there is no lunch break, and only one truck variant is available (which has the highest capacities). The number of duplicated truck variants, i.e., the minimum number of vehicles, is defined by the total demand divided by the maximum load capacity. If the problem is infeasible, that means that either overnight charging is not enough to conclude the route or the time is too strict for the minimum number of vehicles. If it is feasible, the list of truck variants can be reduced to the two closest battery capacities of the total energy consumed to complete the route divided by the number of vehicles. This iterative process continues by gathering information about the problem and adapting the model to the needs until it reaches the complete model or when an optimal solution of a simplified version is good enough.

Although this model can solve larger problems than the complete model, it is still sensible to large problems and is highly dependent on the variant capacities. The easier it is for a variant to complete the route, the faster an optimal solution is found.

5.3.2 Hybrid model

This model is a combination of a VRPTW with a Microsoft Excel spreadsheet that takes the output of the VRPTW and all cost parameters as input. The possibility to charge en route is removed and the problem is limited to a single truck with enough battery capacity (even if not realistic) and realistic load capacity to complete the route. By doing this, it is possible to find optimal solutions for considerable larger problems. There is still, though, the option of the lunch break. This VRPTW still has the TCO as the minimisation objective and provides the total route distance, total route duration and the average powertrain energy consumption $[Wh/m]$. On this work, the powertrain energy consumption is defined as the energy consumed by vehicle's powertrain only, not considering electronic and auxiliary systems. In case more than one vehicle is required, this information is collected per vehicle together with the total load and service duration.

The spreadsheet has two models. The first model calculates the required charging and gives as an output the most cost-effective battery capacity. Then, it provides the TCO for the two closest battery capacities based on the battery pack size of the truck variants being analysed. That means, if the optimal battery capacity is 125 kWh and the battery pack size is 50 kWh, the two variants analysed have the battery capacity of 100 kWh and 150 kWh. The truck variant with the immediately lower battery capacity (100 kWh in the example) will require an extra charge to compensate for the savings on battery size, whereas the immediately higher battery capacity (150 kWh in the example) may have savings from charging as it has more capacity than the optimal one (125 kWh in the example). The second model does the opposite. It takes the battery capacity as input and provides the required charging amount and final TCO as output.

With the VRPTW output, a significant part of the uncertainty of the problem analysis is removed. As all costs are deterministic and dependant on themselves or the VRP output, the only decision left to make is the charging strategy. From the explanation in the section 3.5, there are four different locations vehicles can charge:

depot, public charging stations, customers, and break locations. The decision of where to charge is guided by the charging stations' availability and cost. The cost of charging is not only the cost per Wh charged but also the time cost while charging and the distance and time cost of the detour required to reach the charging station. Nevertheless, these two extra costs are only present in public charging stations (section 3.5). The cost of time charging is equivalent to the energy cost of the vehicle's system power and the detour cost is equivalent to the average distance to a public charging station and the average route speed (given by the VRP).

To decide on the charging strategy, the vehicle acquisition cost is broken into two costs: base acquisition price [SEK] and battery cost [SEK/kWh]. Besides, the total cost of charging [SEK/kWh] is discounted over the whole period of analysis. As a result, the cost of charging is comparable with the battery cost and the charging strategy decision becomes straightforward. As long as the charging option is cheaper than extra battery capacity, the model charges for the maximum amount possible considering the time available at that location. The logic is the same for both spreadsheet models. This may lead to a negative most cost-effective battery capacity (spreadsheet first model). This means that charging is cheaper than more battery capacity and the amount of time available allows to select the lowest possible capacity.

The advantages of this model are the possibility to handle larger problems and flexibility. As it is on a spreadsheet, it is easy to perform a large amount of scenario and sensitivity analyses. Therefore, this is the best model to use if there is limited information available about the customer requirements and operations. For instance, just the total daily mileage and the region the vehicle would be used. The VRPTW can be a support to give a good estimation of powertrain energy consumption from a generic created route within the region. On the other hand, the detour cost is an approximation and the model cannot handle cases where the charging rate, cost of the charging stations and the battery cost vary significantly, since only the average is used. Besides, the availability of the charging stations is only generally assessed by accounting for the number of stops at charging stations required based on the needed charge en route and the net battery capacity.

5.3.3 Ant Colony Optimization model

This model creates the HEVRPTW with semi-public charging stations and lunch break of the complete model using meta-heuristics. It is based on Mavrovouniotis et al. (2019) that used the $\mathcal{MAX}-\mathcal{MIN}$ Ant System ($\mathcal{MM}$AS) where each ant represents a vehicle. Since the main objective is to compare with the complete model, it was also done in AIMMS. Analysing and optimising the computational time is not part of the scope of this work, since it would be significantly more efficient if implemented in another language like Python or C, as it is done in the literature. Nevertheless, Mavrovouniotis et al. (2019) reach the best solutions in a matter of seconds, without parallelism. Therefore, the advantage of this model is the possibility of handling any problem size within a reasonable time. The disadvantage is that the solution is not optimal, efficiency depends on the algorithm implementation, and it requires hyperparameters tuning. The ACO algorithm and the explanation of its functions are presented in the following sections.

Main algorithm ACO-HEVRPTW

```
% Generate initial solution and initialise pheromone trails
InitialisePheromoneTrails
OptimiseVehicleVariants
while ( iteration limit is not reached ) do
    % Find iteration best solution
    while ( colony iteration limit is not reached ) do
        ConstructSolutions
        OptimiseVehicleVariants
        if ( C^i < C^ib ) then
            C^ib ← C^i
        end
    end
    % Check best so far solution
    if ( C^ib < C^bs ) then
        C^bs ← C^ib
    end
    UpdatePheromoneTrails
    ResetPheromoneStagnation
end
```

5.3.3.1 Initialisation

In order to start the algorithm, the pheromone trails τ for the virtual ants has to be initialised. The initial solution generated follows a greedy algorithm in which the next node to be visited is the cheapest. This initial solution is actually a TSP, but it is good enough to start the ant system. Hence, the initial pheromone trail is:

$$\tau_0 = 1/\rho C_0 \qquad \forall (i,j) \in \mathcal{N} \quad (5.35)$$

where τ_0 is the initial pheromone value for all possible paths (i,j), ρ is the pheromone evaporation rate and C_0 is the TCO for the initial route. For this solution, the acquisition price is the base acquisition price and the battery cost for the total energy required to complete the TSP.

5.3.3.2 Optimising the fleet size and variants

As each vehicle in the fleet can be different from the other, the most cost-effective vehicle has to be identified. Hence, the optimal fleet size is calculated and optimal vehicle variants are selected after constructing any solution. This is done by considering the load (weight and volume) and battery capacities available. First, the vehicle's variants that maximise the truckload based on the total demand are selected. For instance, if the total demand is 10t and there are trucks of 6t and 8t, the optimal fleet is composed of two 6t. If the total demand is 14t, one 8t and one 6t.

Second, the optimal battery capacity is selected based on the cost of battery capacity in comparison with the cost of charging at different charging stations, as explained in the section 5.3.2. If charging at public charging stations is cheaper, the lowest battery capacity is selected. Otherwise, the semi-public and break location charging stations are evaluated. If a charging station cost is lower than the capacity cost, then the whole available time to charge is used. The optimal battery capacity is the lowest capacity that is higher than the total energy of the calculated solution subtracted by the total charge amount from semi-public and break location charging stations.

This process is done by each vehicle used and the variant selected is the one that has both the load and battery capacity calculated. If no variant has this combination, the cheapest variant with the same battery capacity but higher load capacity is selected. The initial solution may not be a feasible solution as there are other constraints that were not considered, such as time, that may increase the fleet size. Therefore, only for the initial solution, extra vehicles are generated for constructing solutions later on. These vehicles have the same battery capacity as the optimal vehicle and the minimum load capacity available among the variants.

5.3.3.3 Constructing solutions

As explained in the section 5.1.2, ants make decisions based on the pheromone trail level. Each decision will lead to the next node until all mandatory nodes are visited or there are no more ants available. The probability which governs the decision of each ant k at node i of selecting the destination node j is defined as:

$$p_{ij}^k = \begin{cases} \dfrac{(\tau_{ij})^\alpha (\eta_{ij})^\beta}{\sum_{l \in \mathcal{N}_i^h} (\tau_{il})^\alpha (\eta_{il})^\beta}, & \text{if } j \in \mathcal{N}_i^h \\ 0, & \text{otherwise} \end{cases} \tag{5.36}$$

where τ_{ij} is the pheromone trail, η_{ij} is the visibility or local heuristic value, α and β controls the relative importance of τ_{ij} and η_{ij}, and $\mathcal{N}_i^h$ is the set of the allowed nodes j that ant k can visit from node i. τ_{ij} is initialised as τ_0 and is updated at the end of each global iteration or reinitialised when stagnation is reached. η_{ij} is based on Dang et al. (2022) and defined as:

$$\eta_{ij} = \frac{1}{c_{ij}(U_i - s_j)} \qquad \forall (i,j) \in \mathcal{N} \tag{5.37}$$

$$s_j \equiv y_i + T_{ij} \tag{5.38}$$

where U_i is the upper bound time windows of node i, y_i is the arrival time at node i, T_{ij} travel time between node i and j, and c_{ij} is the *path operational cost*, a simplified version of the total cost of ownership calculation considering operational cost and the battery capacity cost:

$$c_{ij} = (E_d W_d P_v + B_n) e_{ij} + (E_x W_d P_v - B_n) \delta_j + (M_t + I_s) W_d P_v D_{ij} \tag{5.39}$$

$$B_n = \frac{B_w}{B_u} (1 - V_s - \frac{(1 - D_p)}{(1 + D_r)^P}) \tag{5.40}$$

where E_d is the electricity price at the depot, E_x is the surplus electricity price for charging en route, W_d is the working days per month, $P_v = \sum_p^P 1/(1 + D_r)^p$ is the present value of monthly discount rate D_r and planning horizon length P, M_t is the maintenance cost per km, I_s is the insurance cost per km, e_{ij} is the energy consumption on arc (i, j), δ_j is the charge amount at node j, D_{ij} is the length of arc (i, j), B_n is the net battery cost per kWh, B_w is the total battery cost per kWh, B_u is the battery utilisation, and V_s is the percentage of vehicle subsidies.

The set of allowed nodes is the nodes that respect the general model constraints. The constraints are:

- Each node can be visited only once
- All customers must be visited
- Only one break location should be visited
- The arriving time at a node must respect its time windows
- Vehicle's load capacity must be equal to or higher than the customer demand
- The vehicle must have enough battery to reach the next node

Here, enough battery means either that the vehicle has enough battery capacity to visit a node (without a charging station) and the closest charging station of that node or enough battery to visit a charging station. Regarding the charging policy, for public charging stations, the vehicle always fully recharges and only charges when it does not have enough battery to visit a customer. The model fully charges the battery for simplification of the charging logic. For semi-public charging stations, the model charges only if one of the conditions is satisfied: the cost of charging is lower than more battery capacity, or the total energy required is higher than the biggest battery and semi-public electricity cost is lower than public. When an ant does not have any more allowed nodes to visit, it will come back to the depot when it has enough battery and close the route. Then, the next ant is called (if there is still more available).

5.3.3.4 Updating pheromone trails

Over time, the best solution is highlighted by higher values of pheromone whereas the less used paths' pheromone evaporates. After each global iteration, the pheromone trail τ_{ij} is updated as follows:

$$\tau_{ij}^{t+1} = (1-\rho)\tau_{ij}^{t} + \Delta\tau_{ij}^{best} \qquad \forall (i,j) \in \mathcal{N} \tag{5.41}$$

$$\Delta\tau_{ij}^{best} = \begin{cases} 1/C^{best}, & \text{if arc } (i,j) \text{ belongs to best solution} \\ 0, & \text{otherwise} \end{cases} \tag{5.42}$$

where C^{best} is the TCO for either the *iteration best* solution C^{ib} or the *best so far* solution C^{bs}. C^{best} is only equal to C^{bs} every fixed number of iterations, otherwise it is equal to C^{ib} (Mavrovouniotis et al., 2019).

Moreover, the pheromone trail τ_{ij} has minimum τ_{min} and maximum τ_{max} values. $\tau_{max} = 1/C^{bs}$, where C^{bs} is equal to C_0 before the first *best so far* solution is found. τ_{min} is set as 2% of τ_{max} for this work.

5.3.3.5 Resetting pheromone trails

It is common for ant systems to converge to a solution and stagnate quickly (Mavrovouniotis et al., 2019). If no improvement on the *best so far* solution is found after a fixed number of iterations, all values of pheromone trails τ_{ij} are reset to τ_{max}.

5.4 Models' summary

This chapter presented four different models for TCO optimisation following the TCO conceptual model elaborated in the section 4.3. All models are based on a routing model (VRP) and a cost model. The complete model is an exact method using linear programming to find optimal solutions. As it is extremely difficult to compute as the problem grows, it may fail to provide solutions within a reasonable time. Therefore, three alternative methods are presented. The simplified model is a modularisation of the complete model. The hybrid model is a combination of a simpler version of the complete model combined with a spreadsheet. The last model is an Ant Colony Optimization, meta-heuristics using Ant Systems (Figure 5.4).

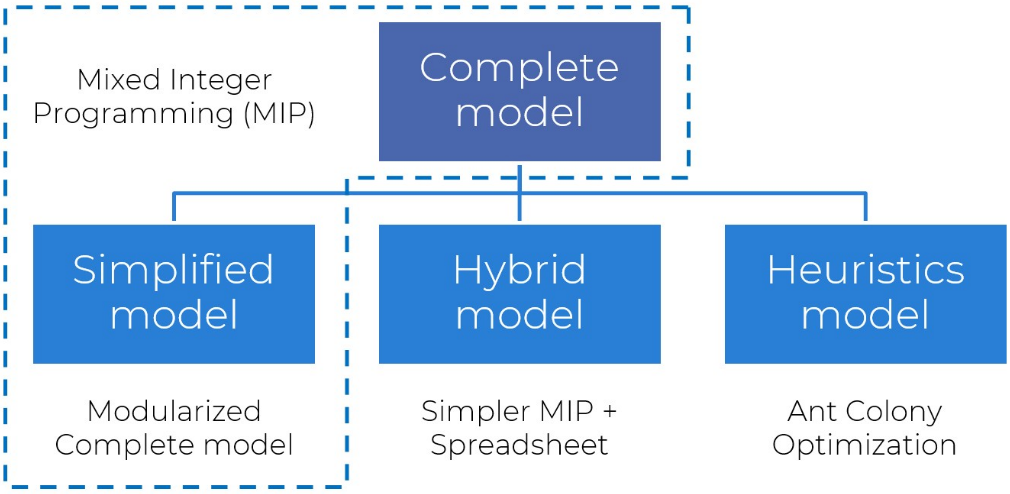

Figure 5.4: Overview of the TCO models proposed.

The complete model is the main model of this work, and it was used to perform all results in the section 6.3 while the spreadsheet model was used to analyse the results. However, the alternative methods exemplify some of the possible paths to follow when dealing with complex real-world applications. Besides, the hybrid model and the ACO model were used to check the validity of the results of the complete model in the section 6.3.5.

6

Model application

In the following section, the model application is demonstrated. First, the required data by the model is listed by their sources. Second, cases to validate the models are presented. Third, the model outputs, cost results and sensitivity analysis from each case are listed and analysed. Finally, the main findings of the results are consolidated and discussed as well as the research questions of this work (section 1.2) are answered.

6.1 Input parameters for data collection

The input parameters for the model were divided into three sources: gathered internally from Volvo, external data from literature or the internet, and assumptions (Table 6.1).

Table 6.1: Input parameters of the TCO model and their source.

Internal	**External**	**Assumption**
Problem coordinates	Charge stations coordinates	Planning horizon
Distance	Charging rate	Working days
Travel time	Charging cost	Working hours
Energy coefficients	Discount rate	Time windows
Demand weight & volume	Infrastructure cost	Battery replacement
Weight & volume capacity	Electricity price	
Battery capacity	Driver cost	
Battery utilisation	Taxes	
Curb weight	Insurance	
Vehicle's system power	Subsidies	
	Depreciation rate	
	Battery density	
	Maintenance cost	
	Acquisition price	
	Service duration	

6.1.1 Internal data

Internal data refers to data or information received directly from Volvo. Table 6.2 shows the internal data and their values for the three cases.

Table 6.2: Internal input data for each case.

Internal data	**Urban**	**Regional**	**Long-haul**
Problem coordinates	Gothenburg	Skåne	Sweden
Demand weight & volume [t, m^3]	7, 69	17, 85	23, 69
Weight & volume capacity [t, m^3]	6/8, 60/80	17, 85	33, 99
Battery pack capacity [kWh]	49	90	90
Battery utilisation	60 %	60 %	60 %
Curb weight [t]	10	20	11
Vehicle's system power [kW]	4	18,8	5,6
Distance, travel time & energy	Node-to-node tool output		

The vehicle specification was battery capacity (depended on the number of battery packs and the battery pack size), weight and volume capacity, battery utilisation, curb weight and vehicle's system power. The vehicle's system power is composed of the auxiliary system power (such as air compressor, pump, heater) and the electric power take-off (ePTO, such as cooling body, refuse compression), which are affected by the size of the truck and temperature. Bigger trucks were used in the regional and long-haul case thus bigger load capacity and system power. Additionally, for the regional case, the trailer was refrigerated that added 13.2kW to the vehicle's system power. The battery utilisation is the portion of the battery that is used to take advantage of the linear charging behaviour (Figure 3.4). It is assumed to be 60% battery utilisation, from 15% to 85% with an additional 10% safety margin. Customer-specific data received from Volvo was the coordinates, demand weight and volume, which varied between cases.

Distance, travel time and energy coefficients were an output from a tool from Volvo based on the framework used by Basso et al. (2021). This tool takes in multiple coordinates and calculates the optimal path between each node. Then, it provides the distance, travel time and energy cost broken down into the energy coefficients α and β between all nodes. The energy consumption prediction considers powertrain energy consumption, acceleration, braking, road inclination, rolling resistance, drag, temperature, traffic between nodes, and regenerative energy from braking.

The tool's calculation of the energy consumption e $[Wh]$ for a certain road uses the following formula:

$$e = \frac{(ad + gdsin(\theta) + gC_r dcos(\theta))m + 0.5C_d A\rho d(v_i^2 + (v_f^2 - v_i^2)/2)}{3600\eta} \tag{6.1}$$

where m is the mass, a is instantaneous acceleration, d represents the total surface distance, g is the gravitational constant $[9.81m/s^2]$, θ is the road inclination, C_r is the rolling resistance, A is the frontal surface are of the vehicle, ρ is air density $[kg/m^3]$, v is instantaneous speed and η is battery-to-wheel efficiency (Basso et al., 2021).

Each path (i,j) is composed of many road links and intersections. For a given path between customers, the mass is constant due to no loading or unloading. Thus, the expected energy consumption of path (i,j) can be calculated by:

$$e_{ij} = \alpha_{ij} m + \beta_{ij} \tag{6.2}$$

where α and β are the energy coefficients.

6.1.2 External data

The data that was not available internally was searched for elsewhere in the literature and other sources. Table 6.3 summarises the values and the sources of the external data for the three cases.

Charging stations in Sweden were found by using ChargeFinder.com. To find accurate charge rate and cost for each charging station, the operator's website was visited if cost information was not updated on ChargeFinder.com. Latitude and longitude coordinates were acquired from Google Maps for the depot, charging stations, break locations, restaurants and groceries retailers. No dummy charging stations were added in the urban case but in the regional and long-haul case dummies stations were added so the truck could visit some charging stations twice if needed. The electricity price for the depot is the result from a calculator at Fortum (2022) where the price for a medium-size company user is fixed for a 12-months contract. From that, it is assumed the price is the same throughout the whole horizon.

The discount rate of 7% is taken from Asplund (2020) for governmental investments in road freight transport in Sweden. The depreciation rate was influenced by the planning horizon and the total mileage. Taefi et al. (2017) calculated it as 50% of the acquisition price for really low mileage and 100% for high mileage, both for a 10-

Table 6.3: Values and sources for external input data.

External data	Value	Source
Coordinates	Latitude, longitude	(Google, 2022)
Charging rate	22-350 kW	(ChargeFinder, 2022; Ljungdahl, 2020)
Charging cost	2.75-5.5 SEK/kWh	(ChargeFinder, 2022; Ljungdahl, 2020)
Discount rate	7%	(Asplund, 2020)
Infrastructure cost	2 000-6 000 SEK/kW	(Basma et al., 2021; Karlström, 2020; Lindgren et al., 2021)
Electricity price	1.13 SEK/kWh	(Fortum, 2022)
Drivers' salary	29 500 SEK/month	(Statistics Sweden, 2022)
Drivers' cost	44 105 SEK/month	(Björn Lundén AB, 2019)
Taxes	≥8 731 SEK/year	(The Swedish Tax Agency, 2022)
Maintenance cost	1.324 SEK/km	(Basma et al., 2021)
Insurance	1.25 SEK/km	(Maibach et al., 2006; Williams & Murrey, 2020)
Subsidies vehicle	20%	(The Swedish Energy Agency, 2020)
Subsidies infrastructure	30%	(Swedish Environmental Protection Agency, 2022)
Depreciation rate	50%-100%	(Taefi et al., 2017; Tanco et al., 2019)
Battery density	110 Wh/kg	(Battery University, 2021)
Battery cost	2 272 SEK/kWh	(Sharpe & Basma, 2022)
Base acquisition price	1 850 000 SEK	(Taefi et al., 2017)
Service duration	∼13 min	(Levandi & Mårdberg, 2016)

years horizon. Besides, Davis and Figliozzi (2013) and Tanco et al. (2019) estimated that 20% of the truck value is left after 10 years for an intermediate mileage. An exponential decay for years and linear decay for mileage of the depreciation rate was created to ensure the model could handle different length of planning horizon and mileage.

The infrastructure cost depended on the operation need for an AC charger (≤22 kW) or a DC fast charger (≥50 kW). The cost for an AC charger was 2 000 SEK/kW, and 6 000 SEK/kW plus 1.2% per year of the initial investment as an operating expense if a DC charger was needed (Basma et al., 2021; Karlström, 2020; Lindgren et al., 2021). Taxes for operating trucks in Sweden were at least 8 731 SEK/year for a medium-sized truck with two axles (as in the urban case) but increased to 13 896 SEK/year for large trucks with more than three axles (The Swedish Tax Agency, 2022). The tax numbers then increased depending on how often tolls gates were passed during a day (The Swedish Tax Agency, 2022). The average driver's salary in Sweden is 29 500 SEK/month, according to Statistics Sweden (2022), but the total driver cost would be 44 105 SEK/month for the average salary because an employer in Sweden needs to pay holiday, insurance and other governmental tax/fees on top of the salary (Björn Lundén AB, 2019).

Insurance cost was calculated as average cost per km in Germany. Insurance cost from Williams and Murrey (2020) in the US was converted to the EU market based on the results from Maibach et al. (2006) where average insurance in Germany was 22% higher than in the US. Maintenance cost had also cost per km and for an average truck in EU (Basma et al., 2021). Subsidies for BEHVs in Sweden are the lowest amount between 20% of the initial price of the BEHV or 40% of the difference in the price of the BEHV and a comparable ICEV (The Swedish Energy Agency, 2020). To simplify, 20% subsidies were always assumed to be the selected one, which means that the comparable ICEV's price is at most 50% of the BEV. Subsidies for non-public charging infrastructure are more subjective and can vary between 30% and 65%, but large companies can only get a maximum of 40% (Swedish Environmental Protection Agency, 2022). It was assumed to be always 30% of the infrastructure investment.

The acquisition cost of trucks depended on the truck type, which varies with the load capacity and battery size. Battery density and battery cost were used to calculate the difference in cost and weight of changing the battery size of the truck. Both battery density and cost were the industry average values. A cost factor for increasing load capacity was used to calculate the cost of larger truck types. The acquisition price for a medium-sized truck was based on (Taefi et al., 2017) which was converted to around 2 million SEK. Based on the battery cost [SEK/kWh], the cumulative inflation in Sweden and the cost projection by (Wu et al., 2015), the base acquisition price, i.e., without battery cost, was around 1.85 million SEK.

Lastly, the expected service time at a customer was taken from Levandi and Mårdberg (2016) thesis where they had gathered data about the time spent in freight distribution with a medium-sized truck. The average time spent was around ten minutes with a standard deviation of six minutes. As it is not normally distributed, a uniform distribution from 5 to 25 min was used to build the cases.

6.1.3 Assumptions

A couple of assumptions were made for the values that there was no internal data available or simply there is not a standard value for it in the literature, but it is particular for each case. They are listed in Table 6.4.

It is assumed that there are at least eight hours available to charge at the depot for the urban case and four hours for the long-haul case but no depot charging at the regional case. For vehicles with a net battery of up to 176 kWh (60% of the total

Table 6.4: Input assumptions and their values.

Input assumption	Urban	Regional	Long-haul
Time to charge at depot	8 h	0 h	4 h
Planning horizon	10 years	10 years	4 years
Working days per year	260	260	260
Working hours	~ 8	~ 8	~ 18
Time windows	Loose	Loose	Loose
Battery replacement	No	No	No

battery capacity of 293 kWh), an AC charger ($\leq$ 22 kWh) is the selected investment for depot charging infrastructure. If the battery is larger, a DC charge is selected. It was assumed that the DC charging infrastructure would be shared by two vehicles, which decreases the infrastructure cost for each vehicle. The DC charging power was calculated based on the battery size and the available time.

The planning horizon (ownership period) was set to 10 years as in many comparable studies for the urban and regional cases. Due to high mileage in the long-haul cases, the planning horizon was decreased to 4 years. Working days per year were assumed to be 260, similarly to other literature and seemed a reasonable number for a whole year of five working days per week. Working hours per day were assumed to be eight hours or longer, already considering the break required for drivers following EU legislation. Truck drivers in the EU have the right for at least 30 minute break after 4.5 hours and can only drive for a maximum of 9 hrs per day (European Union, 2021).

The time windows for each destination to deliver and charge were left loose, that is, all nodes can be visited at any time during the shift. This leaves more flexibility for the model to choose optimal routes, as strict time windows may lead to a single possible solution or even an infeasible problem. For the break, the time windows were defined according to the legislative requirement. The battery replacement was set to zero as it is assumed that the battery replacement would not be required for the planning horizons selected.

6.2 Cases

The cases created were used to validate the models. Three cases were created for analysis: urban distribution, regional distribution and long-haul distribution. These cases were selected as they normally have different average speed and daily mileage.

All operations are within Sweden. The input values and sources or assumptions used in the cases are presented and explained in the section 6.1.

The urban distribution case aimed at serving restaurants and groceries retailers in the Gothenburg area. The vehicle started the tour from a depot and returned to the same depot. The location of the depot was assumed to be in the Bäckebol area in Gothenburg. Fifteen client locations were selected but some of these locations were assumed to have from two up to five clients, leading to a total of 29 clients. Seven charging stations were selected based on the location that was not far from clients visually on a map. The maximum route duration was set to 35 100s (9.75h) where the total demand of the clients was around seven tonnes.

Eight truck variants were defined for the model to choose from. The eight variants were created by a combination of load capacity and the number of battery packs. The volume capacity was either 60 or 80 m^3 and the number of the battery packs was three, four, five or six of 49 kWh. The curb weight and weight capacity depended on the number of battery packs. The price depended on the number of battery packs and volume capacity. Table 6.5 shows the variants available for the urban case.

Table 6.5: Price, weight, volume and battery capacity, and curb weight of vehicle variants available for the urban case.

Variant	1	2	3	4	5	6	7	8
Price [SEK]	2 517 968	2 406 640	2 295 312	2 183 984	2 189 537	2 092 730	1 995 923	1 899 117
Weight cap [kg]	8 000	8 445	8 890	9 335	6 000	6 445	6 890	7 335
Volume cap [dm^3]	80 000	80 000	80 000	80 000	60 000	60 000	60 000	60 000
Battery cap [Wh]	294 000	245 000	196 000	147 000	294 000	245 000	196 000	147 000
Curb weight [kg]	10 000	9 555	9 110	8 665	10 000	9 555	9 110	8 665

The regional case aimed at serving groceries retailers with cooled products in Skåne County. The depot was located in Helsingborg while three customers were located around the county. Three charging stations near the customers or in the expected route were selected. Dummies were added, so there were six charging stations. The maximum route duration was set to 28 800s (8h) where the total demand of the clients was around 17t. No charging stations were at the depot or customers.

Two truck variants were defined for the model to choose from. The two model variants were created by a combination of at least 17t weight capacity (85 m^3 volume capacity) and five or six battery packs. The trucks were a tractor and a refrigerated trailer. The capacity of each battery pack was 90 kWh. Table 6.6 shows the variants available for the regional case.

Table 6.6: Price, weight, volume and battery capacity, and curb weight of vehicle variants available for the regional case.

Variant	**1**	**2**
Price [SEK]	3 076 880	2 872 400
Weight cap [kg]	17 000	17 818
Volume cap [dm^3]	85 000	85 000
Battery cap [Wh]	540 000	450 000
Curb weight	20 000	19 182

The long-haul case aimed at delivering from a warehouse in Gothenburg (depot) to a warehouse in Stockholm and back to Gothenburg. As the driving of the route takes more than 9 hours, two drivers were required to comply with EU regulations for road transport workers (European Union, 2021). Thirteen charging stations on possible routes from Gothenburg to Stockholm were added with their dummies, with a total of 26 charging stations. The maximum route duration was set to 70200s (19.5h) where the total demand was around 23 tonnes. There was an available 162 kWh charging station at the warehouse in Stockholm to use while loading and unloading.

Four truck variants were created in this case. They had at least 33t weight capacity (99 m^3 volume capacity) and three to six battery packs of 90 kWh. The truck was a tractor and a trailer. Table 6.7 shows the variants available for the long-haul case.

Table 6.7: Price, weight, volume and battery capacity, and curb weight of vehicle variants available for the long-haul case.

Variant	**1**	**2**	**3**	**4**
Price [SEK]	3 076 880	2 872 400	2 667 920	2 463 440
Weight cap [kg]	33 000	33 818	34 636	35 454
Volume cap [dm^3]	99 000	99 000	99 000	99 000
Battery cap [Wh]	540 000	450 000	360 000	270 000
Curb weight	11 000	10 182	9 364	8 546

6.3 Cases' results

In this section, the results of the cases using the models are presented, analysed and discussed. First, the results will be presented case by case. For each case, it will be presented on a map, its key route characteristic and key cost outputs, sensitivity analyses and a short discussion of the results. Second, the main findings of the cases will be summarised, and similarities and contrasts will be discussed. Lastly, a comparison of each model's results will be presented and discussed.

The key route characteristics and outputs are from the best solution found. The solution of the urban case was optimal and found with the simplified model. The solution of the regional case was also optimal but found by the complete model. However, the solution for the long-haul case is the best solution found after 20 minutes with the complete model. Thus, it is not guaranteed to be optimal as the optimisation was interrupted.

The results contain the total distance of the route and the total duration it takes depending on constraints and input data from section 6.2. The energy that the truck(s) spends on the route is broken down into energy due to driving and due to the vehicle system's consumption. The charged amount the model decides to charge on the route, if any, is shown together with the charging time needed at the depot to have a full net battery capacity for the next day. The model also returns the number of vehicles needed and what variants were selected for the vehicles used by the model. The cost outputs are broken down into sub costs for each TCO temporal phase following Figure 4.1. Additionally, the percentage of each cost factor is given to reflect what are the most influential one.

Sensitivity analysis was conducted on key input parameters and outputs with the spreadsheet model. The key input parameters analysed were: the number of periods of the planning horizon (ownership period), discount rate, depot and public electricity price, battery SOC utilisation and vehicle system power consumption (auxiliary and ePTO). The key model outputs analysed were the powertrain energy consumption, total distance and duration. The selected parameters and outputs were increased and decreased by 20% while keeping other parameters fixed.

6.3.1 Urban case

Visual presentation on a map of the location of urban case depot, customers, charging stations and break locations visited are presented in Figure 6.1. The main characteristics of the optimal route in the urban case are shown in the Table 6.8.

The cost outputs for the urban case are presented in the Table 6.9. The ownership cost accounts for 68.7% of the TCO with driver cost alone accounting for 65.7%. Initial cost accounts for 30.5%, operation cost is only 6.5% and end-of-life cost is -5.7% of the TCO (positive cash flow).

Sensitivity analysis of the key input parameters and some output numbers of the

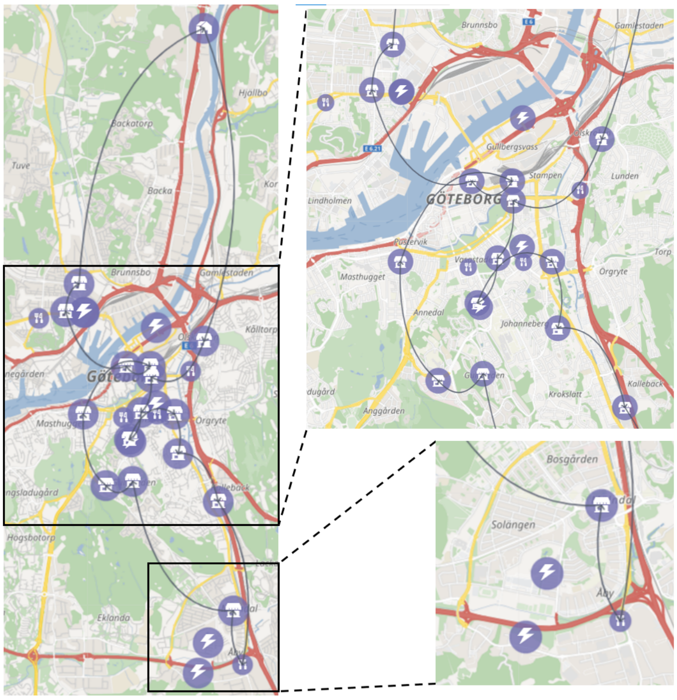

Figure 6.1: Graphic overview of the urban case. The depot is on the north, customers are the *store icon*, charging stations are the *lightning icon* and break locations are the *fork and knife icon*.

Table 6.8: Numerical results for the urban case of the best route and the vehicle selected.

Route characteristics (per day)		
Total distance	46.9	km
Total duration	09:17	hh:mm
Total service duration	06:39	hh:mm
Total demand delivered	6.9	t
Average speed	25.0	km/h
Energy due to driving	34.0	kWh
Powertrain consumption	0.73	kWh/km
Energy vehicle system	37.1	kWh
Total energy consumption	71.2	kWh
Charging en route	0	kWh
Depot charging time	03:14	hh:mm
Specifications of vehicle(s) selected		
Number of vehicles	1	
Weight capacity	9.3	t
Curb weight	8.7	t
Total battery capacity	147	kWh

Table 6.9: Cost outputs and TCO result for the urban case

Cost	**SEK**	**%**
Purchase cost	2 183 984	37.4%
Infrastructure cost	44 000	0.8%
Vehicle subsidies	-436 797	-7.5%
Infrastructure subsidies	-13 200	-0.2%
Total initial cost	**1 777 987**	**30.5%**
Energy cost	151 512	2.6%
Maintenance cost	117 098	2.0%
Insurance cost	110 553	1.9%
Total operation cost	**379 163**	**6.5%**
Driver cost	3 835 107	65.7%
Taxes cost	176 307	3.0%
Total ownership cost	**4 011 414**	**68.7%**
Resale value	-333 068	-5.7%
Total end-of-life cost	**-333 068**	**-5.7%**
TCO	**5 835 496**	**100%**

optimal route results for the urban case is shown in Table 6.10. There is no value for a 20% increase in the number of periods as it was assumed that the current number of periods is the maximum number of periods possible for the case. There is no ePTO consumption for the truck in the urban case and therefore is no sensitivity analysis conducted for it.

6.3.1.1 Case discussion

By far, the two most impactful costs on the TCO, in the urban case, are the driver cost (65.7%) and total vehicles cost (29.9%, purchase cost + vehicle subsidies). Interestingly the energy cost is only 2.6% of the TCO, but energy is usually a central variable when considering the cost for vehicles (Delucchi & Lipman, 2001). The driver cost is a high proportion of the TCO, even with the model limiting the number of vehicles to only one. Lastly, the purchase cost magnitude in the urban case reflects the main challenge of BEVs, the high initial cost (Morganti & Browne, 2018).

The purchase cost varies by battery size in the urban case (Table 6.5) and it has a high impact on the TCO to take a bigger battery. This is supported by the results from Taefi et al. (2017). For them, battery size, battery price and residual value

Table 6.10: Results for sensitivity analysis on TCO for the urban case. Most values are varied -/+ 20%, except for the discount rate which varies -/+ 2%.

	TCO change	
Parameters {-20%, +20%}		
Number of Periods	-11.0%	-
Discount rate {-2%, +2%}	5.8%	-4.4%
Depot electricity cost	-0.5%	1.0%
Public electricity cost	0%	0%
Battery SOC utilisation	2.2%	0%
Auxiliary consumption	-0.3%	0.3%
ePTO consumption	-	-
Model outputs {-20%, +20%}		
Powertrain consumption	-0.2%	0.3%
Total distance	-1.0%	1.1%
Total duration	-0.3%	0.3%

were most sensitive to the TCO of trucks in low mileage scenarios, where drivers' cost was not considered.

From the sensitivity analysis, only two parameters/outputs had around 5% or more impact on TCO: number of periods and discount rate. Both are input parameters where the number of periods magnifies the monthly cost like driver cost and discount rate. It is important that they are as accurate as possible for the urban case due to the high effect on TCO.

6.3.2 Regional case

Visual presentation on a map of the location of regional case depot, customers and charging stations are presented in Figure 6.2. The output of the characteristics of the optimal route for the regional case is presented in the Table 6.11.

The cost outputs for the regional case are presented in the Table 6.12. The operation cost accounts for 48.0% of the TCO with energy cost alone accounting for 38.6%. Initial cost accounts for 18.8% and ownership cost 33.1% of the TCO.

Sensitivity analysis of the key input parameters and some output numbers of the optimal route results for the regional case is shown in Table 6.13. There is no value for a 20% increase in the number of periods as it was assumed that the current number of periods is the maximum number for the case. Also, there is not any

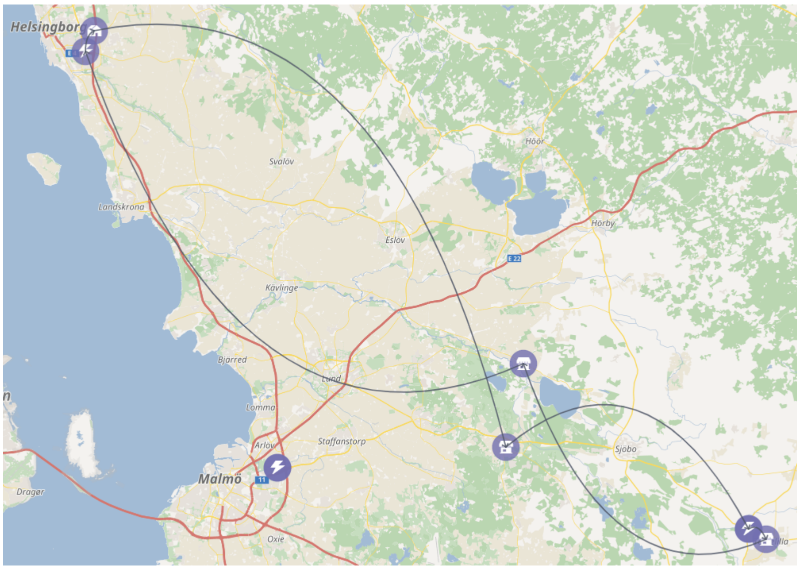

Figure 6.2: Graphic overview of the regional case. The depot is on the north, customers are the *store icon* and charging stations are the *lightning icon*.

Table 6.11: Numerical results for the regional case of the best route and the vehicle selected.

Route characteristics (per day)		
Total distance	237.2	km
Total duration	05:55	hh:mm
Total service duration	00:30	hh:mm
Total demand delivered	17.0	t
Average speed	51.8	km/h
Energy due to driving	343.9	kWh
Powertrain consumption	1.45	kWh/km
Energy vehicle system	111.4	kWh
Total energy consumption	455.3	kWh
Charging en route	423.2	kWh
Depot charging time	-	hh:mm
Vehicle(s) specifications		
Number of vehicles	1	
Weight capacity	17.8	t
Curb weight	19.2	t
Total battery capacity	450	kWh

Table 6.12: Cost outputs and TCO result for the regional case.

Cost	**SEK**	**%**
Purchase cost	2 872 400	23.5%
Infrastructure cost	0	0.0%
Vehicle subsidies	-574 480	-4.7%
Infrastructure subsidies	0	-0.0%
Total initial cost	**2 297 920**	**18.8%**
Energy cost	4 717 529	38.6%
Maintenance cost	591 729	4.8%
Insurance cost	558 657	4.6%
Total operation cost	**5 867 915**	**48.0%**
Driver cost	3 835 107	31.4%
Taxes cost	213 733	1.7%
Total ownership cost	**4 048 840**	**33.1%**
Resale value	0	0%
Total end-of-life cost	**0**	**0%**
TCO	**12 214 675**	**100%**

charging station at the depot in the regional case, hence no depot electricity price.

6.3.2.1 Case discussion

The three most impactful costs on the TCO, in the regional case, are the energy cost (38.6%), driver cost (31.4%), and total vehicles cost (18.8%, purchase cost + vehicle subsidies). Here, the energy cost is one of the central variables for the TCO of trucks similar to what Delucchi and Lipman (2001) found. Electricity price and energy consumption, components of energy cost, was also the most impactful parameter in Taefi et al. (2017) paper for high mileage scenario similar to the regional case.

From the sensitivity analysis, four parameters/outputs had around 5% or more impact on TCO, number of periods, discount rate, powertrain consumption and total distance. The number of periods has a high impact in the regional case as the operation cost that increases or decreases with the number of periods accounts for 48.0% of the TCO for ten years. Similarly, as a large part of the cost happens throughout the ten-years planning horizon, the majority of the cost is discounted, by using the discount rate, to the present value. The powertrain consumption and total distance depend on the optimal solution. If some change of context (such as geographical location and cost of capital) happened that affected these outputs, it

Table 6.13: Results for sensitivity analysis on TCO for the regional case. Most values are varied -/+ 20%, except for the discount rate which varies -/+ 2%.

	TCO change	
Parameters {-20%, +20%}		
Number of Periods	-11.5%	-
Discount rate {-2%, +2%}	7.3%	-6.4%
Depot electricity cost	-	-
Public electricity cost	-2.7%	3.3%
Battery SOC utilisation	0%	0%
Auxiliary consumption	-0.4%	0.4%
ePTO consumption	-1.2%	1.4%
Model outputs {-20%, +20%}		
Powertrain consumption	-5.8%	6.1%
Total distance	-8.7%	9.6%
Total duration	-1.8%	2.0%

would have a high impact on the TCO.

6.3.3 Long-haul case

Visual presentation on a map of the location of the long-haul case depot, customers and charging stations are presented in Figure 6.3. The output of the characteristics of the optimal route for the long-haul case is presented in Table 6.14.

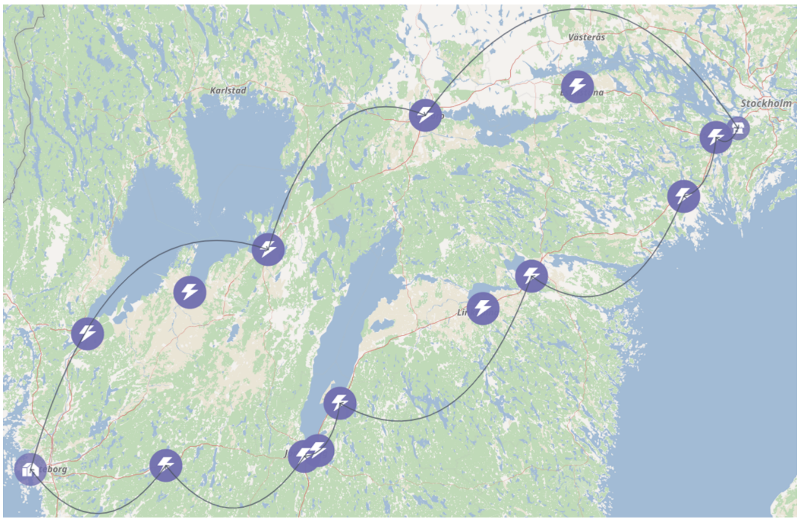

Figure 6.3: Graphic overview of the long-haul case.

The cost outputs for the long-haul case are presented in the Table 6.15. The operation cost accounts for 49.4% of the TCO with energy cost alone accounting for

Table 6.14: Numerical results for the long-haul case of the best route and the vehicle selected.

Route characteristics (per day)		
Total distance	937.3	km
Total duration	16:51	hh:mm
Total service duration	01:53	hh:mm
Total demand delivered	23.1	t
Average speed	80.1	km/h
Energy due to driving	1 526.7	kWh
Power train consumption	1.63	kWh/km
Energy vehicle System	94.4	kWh
Total energy consumption	1 621.1	kWh
Charging en route	1 297.1	kWh
Depot charging time	01:48	hh:mm
Vehicle(s) specifications		
Number of vehicles	1	
Weight capacity	33.0	t
Curb weight	11.0	t
Total battery capacity	540	kWh

32.3%. Initial cost accounts for 20.9% and ownership cost 29.7% of the TCO.

Sensitivity analysis of the key input parameters and some output numbers of the optimal route results for the long-haul case is shown in the Table 6.16. There is no value for a 20% increase in the number of periods as it was assumed that the current number of periods is the maximum number of periods possible for the case. There is no ePTO consumption for the truck in the long-haul case and therefore no sensitivity analysis is conducted for it.

6.3.3.1 Case discussion

Similar to the regional case, the most impactful costs are energy cost (32.3%), driver cost (28.9%) and total vehicles cost (19.2%, purchase cost + vehicle subsidies). The energy cost proportion is not as high as in the regional case but is also a central cost variable for the case. The purchase cost would be higher if a more expensive truck was available. As a truck with a bigger battery is not available, the vehicle does not go more than 200 kilometres on the route without needing to stop to charge. Moreover, increasing the weight demand makes the problem infeasible. The weight increase entails higher energy consumption, thus extra charging time is needed. As

Table 6.15: Cost outputs and TCO result for the long-haul case.

Cost	**SEK**	**%**
Purchase cost	3 076 880	24.0%
Infrastructure cost	506 269	4.0%
Vehicle subsidies	-615 376	-4.8%
Infrastructure subsidies	-291 600	-2.3%
Total initial cost	**2 676 173**	**20.9%**
Energy cost	4 132 932	32.3%
Maintenance cost	1 127 597	8.8%
Insurance cost	1 064 574	8.3%
Total operation cost	**6 325 103**	**49.4%**
Driver cost	3 699 058	28.9%
Taxes cost	111 043	0.9%
Total ownership cost	**3 810 101**	**29.7%**
Resale value	0	0%
Total end-of-life cost	**0**	**0%**
TCO	**12 811 378**	**100%**

Table 6.16: Results for sensitivity analysis on TCO for the long-haul case. Most values are varied -/+ 20%, except for the discount rate which varies -/+ 2%.

	TCO change	
Parameters {-20%, +20%}		
Number of Periods	-13.5%	-
Discount rate {-2%, +2%}	3.0%	-2.8%
Depot electricity cost	-0.5%	0.6%
Public electricity cost	-5.4%	6.0%
Battery SOC utilisation	1.3%	-1.3%
Auxiliary consumption	-0.3%	0.3%
ePTO consumption	-	-
Model outputs {-20%, +20%}		
Power train consumption	-7.6%	7.9%
Total distance	-10.8%	11.9%
Total duration	-0.4%	0.5%

a result, the vehicle cannot complete the route with the available battery capacity and charging stations.

The results of the sensitivity analysis are similar to the one from the regional case except that the long-haul case is not as sensitive to the discount rate and is more sensitive to public electricity cost. The reason for that is that the period is only 4 years compared to 10 years in the other cases for the discount rate while the daily charging en route is more than double compared to the regional case.

6.3.4 Cases comparison

The relative importance of each cost for each case is compiled in Figure 6.4. All cases have in common that the initial cost is one of the main cost drivers and especially in the urban case where it is roughly twice more relevant than in the other cases. The results of the regional and long-haul cases are similar but the long-haul case could be considered a more extreme version of the regional one. The long-haul route distance and duration are about twice as long with a little higher average speed but without a cooling unit. The cooling body significantly increases not only the vehicle system's energy consumption but also the powertrain energy consumption due to the extra curb weight, which could explain why the powertrain energy consumption in the regional case is almost as high as in the long-haul.

On the other hand, the powertrain consumption for the urban case is way lower than in the other cases as the total weight and average speed are considerably lower. Weight and volume greatly affect the energy between nodes, which was shown in Equation 6.2. The low energy cost of the urban case, compared to the other cases, is due to the efficient powertrain energy consumption and shorter distance, along with only using the depot charging which is three to five-time cheaper than charging en route (see Table 6.3).

The ownership cost, which is mainly driven by the driver cost, also greatly varies between the urban case and the other two. Even though there are two drivers needed (due to EU regulation) and a triple longer operation time for the long-haul case compared to the regional, the driver cost proportion of the total cost is the same. Only the urban case has end-of-life cost (which is revenue in this case) due to its low mileage.

The TCO in all cases is sensitive to changes in the number of periods and discount

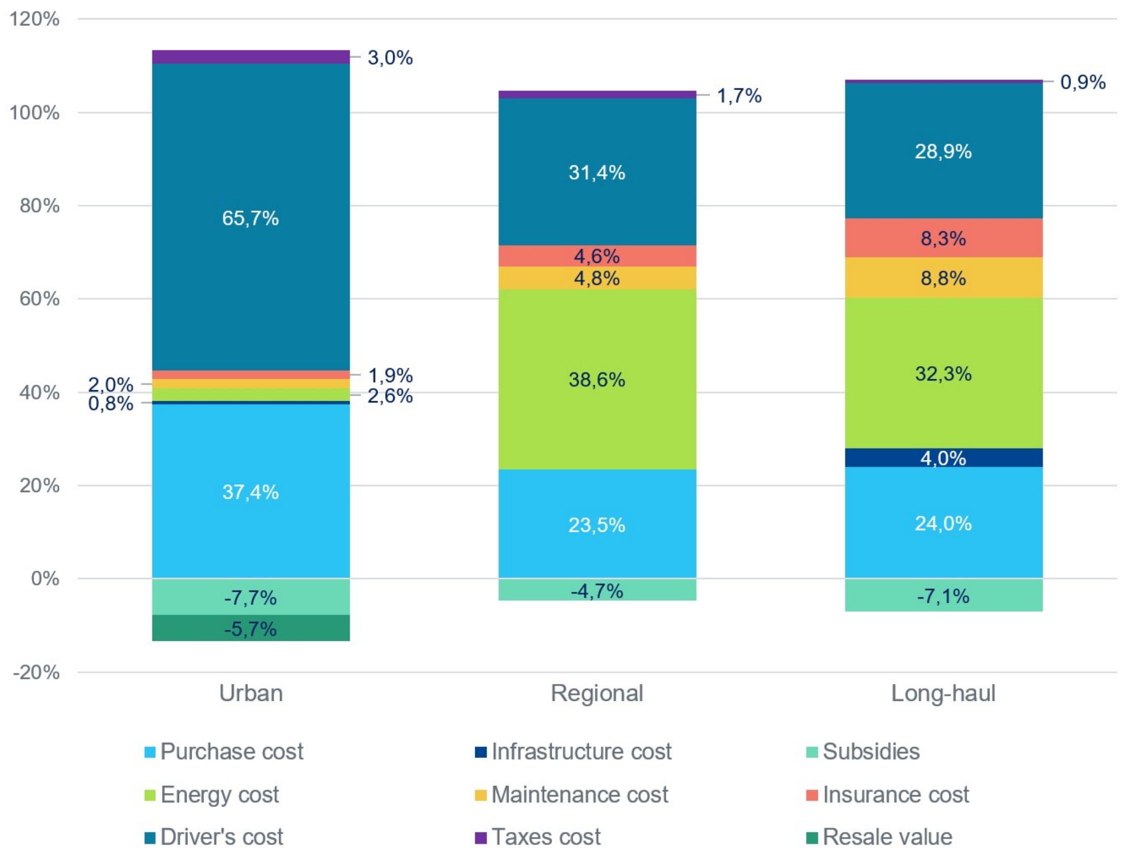

Figure 6.4: Proportion of each TCO cost dimension for each case.

rate. This is due to how the model calculates the TCO. Every cost except the initial cost is discounted to present value throughout the number of periods. Hence, the higher those costs are, the more TCO is affected by the number of periods. The discount rate will therefore have more impact with a higher number of periods and with higher operational and ownership costs.

The main difference in the sensitivity analysis of the cases is when it comes to the sensitivity of TCO to auxiliary consumption, powertrain consumption and total distance. The urban case was not sensitive to them while the regional and long-haul cases were sensitive. All these parameters/outputs are interconnected when it comes to the TCO calculations as they affect the energy requirement that directly affects the energy cost. The main difference between the urban case and the regional and long-haul case was higher mileage and load in the latter ones, which make the cases more sensitive to the previously mentioned parameters/outputs.

Finally, as can be seen in the Table 6.17, depending on how the TCO value is calculated, different conclusions can be made. Whereas the regional and long-haul cases have similar TCO, if analysed by year, the latter is 2.6 times higher than the former. Nevertheless, when considering the daily route distance, the urban case is almost 3.7 times more expensive than the long-haul and the situation with the regional is inverted, 2.4 times more expensive (in comparison with 2 times cheaper before). This difference in the TCO unit depends on the comparison which is being made. Danielis et al. (2018) and Wu et al. (2015) used TCO/km when comparing various vehicles with similar application while Davis and Figliozzi (2013), Taefi et al. (2017), and Tanco et al. (2019) used TCO to compare similar trucks but different applications such as different mileage per day.

Table 6.17: Comparison of TCO, TCO per year and TCO per year per daily km for each case in SEK.

	Urban case	**Regional case**	**Long-haul case**
TCO	5 835 496	12 214 675	12 811 378
TCO/year	583 550	1 221 467	3 202 844
TCO/year/km	12 431	5 149	3 417

6.3.5 Models comparison

Table 6.19 compares the main outputs provided by each model. The hyperparameter setting used at the ACO is stated in Table 6.18. α and β are part of the equation (5.36), ρ is on equation (5.41), 50 iterations are done to select the iteration best, the pheromone is only updated with the best solution every 25 iterations, and 50 iterations without change in the best so far solution found is the stagnation criteria.

Table 6.18: Hyperparameters setting for the ACO model.

Parameter	**Value**	**Parameter**	**Value**
α	1	Colony iterations	50
β	3	Best solution update	25
ρ	0.2	Stagnation criteria	50

The lowest TCO is always given by the complete model, however, the difference between it and the other models' TCO is considerably small (from 0.1% to 2.4%), sometimes even finding the same route, and the vehicle variant selected is the same. This validates the models' implementation and the difference in output can be stated as the performance of the model.

Due to the simplifications in the routing and the estimation of the charging required en route, the hybrid model seems to overestimate the TCO, which is expected. As

Table 6.19: Key outputs of each model for each case.

	Complete	Hybrid	ACO
URBAN CASE			
Total distance [km]	46.9	46.9	47.9
Total duration [hh:mm]	09:17	09:17	09:28
Power train consumption [kW/km]	0.73	0.73	0.68
Total energy consumption [kW]	71.2	71.2	70.7
Charging en route [kW]	0	0	0
TCO [SEK]	**5 835 496**	**5 835 496**	**5 839 366**
REGIONAL CASE	**Complete**	**Hybrid**	**ACO**
Total distance [km]	237.2	234.6	237.2
Total duration [hh:mm]	05:55	05:02	06:12
Power train consumption [kW/km]	1.45	1.47	1.45
Total energy consumption [kW]	455 269	439 611	460 319
Charging en route [kW]	423.2	433.4	454.4
TCO [SEK]	**12 214 675**	**12 230 057**	**12 230 098**
LONG-HAUL CASE	**Complete**	**Hybrid**	**ACO**
Total distance [km]	937.3	925.0	943.1
Total duration [hh:mm]	16:51	12:12	16:53
Power train consumption [kW/km]	1.63	1.66	1.57
Total energy consumption [kW]	1 621.1	1 603.4	1 570.5
Charging en route [kW]	1 297.1	1 279.4	1 287.6
TCO [SEK]	**12 811 378**	**13 124 361**	**12 896 795**

discussed in the section 3.5, there are detour and charge time costs associated with opportunistic charging. Also, the most optimal path might be hillier or allow to drive at a higher speed, than the path to reach the charging stations, leading to a higher powertrain energy consumption. On the contrary, the ACO model is the model that most optimises the powertrain consumption, finding more energy efficient routes than the other models. However, the total distance is not as optimised as well as the amount charged, which may have led to a more expensive solution.

It is worth noting that the computational time for the hybrid model is either the same or considerably lower than the complete model as it is only a VRPTW optimisation and adding the output into the spreadsheet model. This model also made it possible to perform fast sensitivity analyses with the results from the complete model. Similarly, the ACO model found its best solution within a couple of minutes even using AIMMS language, whereas the long-haul case in the complete model ran for 20 minutes. Therefore, it is worth exploring the potential of the alternative methods to provide good enough solutions for complex real-world cases in a reasonable time.

6.4 Discussion

This section encompasses the discussion of the results presented in the previous section. Besides, cross references with previous report sections as well as similarities and differences in comparison with previous research are highlighted. First, the major findings are presented while answering the first four research questions presented in section 1.2. Second, the findings regarding the supply chain impact are presented, which are related to the last research question. Third, the models' contributions to the purchase/selling process of BEHVs are highlighted. Lastly, other potential applications of the proposed models are discussed.

6.4.1 Main findings

From the literature review, several cost dimensions were present in most of the previous research deemed as relevant for a comprehensive TCO (Figure 3.6). This leads to our RQ.1:

RQ.1. What are the main dimensions of TCO of BEHVs?

The final TCO conceptual model presented in the Figure 4.1 encompasses almost all dimensions found in the literature review, except for battery degradation due to little conclusive research on the topic and high complexity. Resale value is also associated in the literature with high uncertainty, however, a parallel can be drawn to ICEVs using depreciation, leading to fair reasonable values. On the other hand, battery degradation depends on a lot more parameters than kilometres or cycles and can present a non-linear behaviour. By disregarding battery degradation, a qualitative analysis of the final vehicle selected is advised to understand, for example, the impact on the amount charged en route (section 6.4.3).

Although there is a general structure for calculating the TCO of durable products (section 3.2), the literature review showed there was little standard on how to calculate the TCO for BEHVs (section 3.3). This seems to be mainly because of the complexity of modelling routing and energy consumption. There is extensive research on both topics, thus, the final model depends on the context in which it will be used. The context defines for example what information is available, what is the time available, the output accuracy and details required. This leads to our RQ.2:

> RQ.2. What are the most relevant analytical models present in the literature to build an accurate TCO model that suits Volvo's context and customers' specific needs?

As Volvo already had an energy consumption prediction tool (section 4.1), making use of it and combining it with an exact method for routing guided the formulation of the analytical model (section 5.2). Nevertheless, at the same time, the model was also required to adapt to the amount of information available to the customer. This could mean a customer has limited information on the operation the truck is intended for, knowing only the daily mileage and demand, for example. In contrast, the customer might have a lot of details but a huge heterogeneous fleet.

The complete model is not able to handle those two examples of customers mentioned above. Without specific route information, it may not be as helpful to use an exact method. For this situation, the hybrid model (section 5.3.2) is one proposed alternative, although it is not present in the literature. For complex operations, exact methods may fail to find any solution, hence, the literature has extensively researched heuristics methods. For this situation, the ACO model (section 5.3.3) is one proposed alternative. However, there is always a trade-off of moving away from exact methods: improved speed and flexibility at the cost of accuracy. Therefore, a single general TCO model is not able to account for the variety of customers' requirements.

This conclusion leads to our RQ.3:

> RQ.3. What is the minimum information needed from the customer to calculate a reasonable accurate TCO?

The complete list of information required to run a comprehensive and detailed analysis is present in the Table 6.1. The more personalised information the customer can provide and the more specific the data is for the operation's region (such as US, EU), the more customised the analysis will be. In case the customer does not have some information, the values presented in the sections 6.1.2 and 6.1.3 can be used as a benchmark, even though some data are specific to Sweden. However, the information related to the route and vehicle (section 6.1.1) should always come from the customer.

The minimum information that the hybrid model requires for the routing model is the geographic region the vehicle(s) will be used, total daily distance, demand and working hours, and information about owned charging infrastructure. For the complete and ACO models, the minimum information required is the visited locations, location-specific demand and loading/unloading duration, as well as working hours and information about owned charging infrastructure.

The information regarding public charging stations' location, rate and cost does not need to come from the customer, as it is widely available. Nonetheless, it is worth knowing if the customer already uses any public charging station or subscribes to a charging service.

Regarding vehicles, the appropriate vehicle variants are selected based on the type of customer operation. Is it delivery of goods? Does it need a cooling body? Or is it refuse collection? This information will guide Volvo to select the suitable vehicle variants that will lead to the vehicle specifications needed by all models.

For the cost part on all models, monthly working days, cost of capital (discount rate) and depot electricity price are the minimum information needed to provide more realistic results for the customer specific situation. However, they are not mandatory as a benchmark can be used instead.

With the required data collected and prepared for each realistic case built, the cost results lead to our RQ.4:

RQ.4. What parameters affect the most the TCO calculation of BEHV?

From Figure 6.4, it is clear that the two main costs are the driver cost followed by the purchase cost. However, as the distance increases, energy cost grows from the fourth-highest cost to the highest cost. This is in accordance with the conclusions of Taefi et al. (2017). Together with driver cost, purchase and energy cost are the most relevant costs. The parameters associated with them significantly affect the TCO, as explained in section 6.3.4. Therefore, TCO is most sensitive to the planning horizon length (ownership period), discount rate and monthly working days, as they affect both driver and energy cost. For high mileage scenarios, the variation of total distance, powertrain energy consumption, and public charging stations' electricity cost also has significant impact on the TCO.

6.4.2 Supply chain impact

The above discussion leads to RQ.5 as the TCO model needs to be able to consider all customers' requirements, including the supply chain:

> RQ.5. How is the proposed TCO model able to assist Volvo in helping customers to have a smooth transition to electromobility regarding supply chain impact?

The models are able to take into account the trade-offs of different battery sizes, summarised in Table 3.6 when selecting the cost-optimal variant. The range and the initial price of BEHVs have been a concern for users of electric vehicles (Kin et al., 2021; Sandén & Wallgren, 2017). Prices of BEHV's variants in the cases were controlled by the size of the battery (see Tables 6.5–6.7) where the prices varied up to 500 000 SEK in the long-haul case when comparing the variant with the biggest and the smallest battery. The range of the trucks in the cases was dependent on battery size but the battery size was subjected to the energy required for the route and charging strategy. The energy required for a route consists of powertrain energy consumption [Wh/m] and system energy power [W]. The powertrain consumption is dependent on the total weight of the truck and the speed. This is evident in the comparison of the urban cases with the other cases (see Section 6.1.1 for more detail). The system energy power is mainly affected by the operation time and if additional energy sources are added, like the refrigerated unit in the regional case. Thus, the range of a certain battery will likely depend on the type of operation as there might be differences in powertrain consumption and system energy power. For instance, the powertrain consumption is different for urban driving and highway driving as the latter involves higher speeds, bigger trucks and more cargo than the former.

The battery size of a BEHV also affects the weight capacity of the vehicle as is evident in the Tables 6.5–6.7. By choosing the smallest battery, the weight capacity increases up to 1.3t in the urban case and up to 2.4t in the long-haul case. In some cases, the decreased weight capacity can decrease the supply chain performance of the trucks as the weight of goods transported is a common KPI measured for trucks (Kin et al., 2021; Kovács, 2017). However, the volume capacity does not change. Hence, the change of battery size would not change vehicle selection if the problem has strict volume demand (light goods such as electronics and furniture). This can be seen in the urban case. Due to the change of weight capacity of smaller battery size, the vehicle variant 8 (Table 6.5) satisfy weight demand of the urban case, but not the volume capacity.

The charging strategy is commonly mentioned when discussing effects on the supply chain (Kin et al., 2021). The model minimises cost based on the route, variants available and charging strategies (depot charging, en route at public or semi-public charging stations). All charging strategies are allowed in the urban and long-haul case but only en route charging at public stations was available in the regional case. In the urban case, the model found out that depot charging was the cheapest strategy which is in line with what Kin et al. (2021) and Pelletier et al. (2016) stated. Charging en route is a more expensive strategy due to higher charging cost and extra distance and time of the detour. The model decided in the long-haul case to use hybrid charging because no truck variant had enough battery capacity to skip charging en route.

In the long-haul and the regional case, the model was dependent on a sufficient supply of charging stations so the problem would be feasible. When all charging stations were removed the HEVRPTW problem became infeasible as the energy to finish the route was higher than any battery capacity available. For the long-haul case, removing part of the charging stations would also make the problem infeasible due to the lack of good charging locations. One of the risks of using or allowing en route charging is the supply of charging options. It was considered in the MEET model when assessing the feasibility of adding an electric truck to the fleet (Sandén & Wallgren, 2017). The data gathering for the model about availability and electricity prices of charging infrastructure (depot, semi-public and public stations) gives the customer and the seller an idea of what charging strategy is most cost-effective and feasible.

One of the most commonly measured KPI of trucks in supply chains is the utilisation of the truck (Kin et al., 2021; Kovács, 2017; Sandén & Wallgren, 2017). There was no charging in the urban case but in the long-haul case, for example, there was considerable charging during working hours (excluding the time when charging during the break of the driver). Out of the total operation time in the long-haul case, roughly 11% of the time is spent charging the vehicle (using 350 kW charging stations), which decreases the vehicle utilisation. The vehicle utilisation could be impacted by the charging power of the charging station. If there were only 150 kW charging stations available, the time spent charging would have increased to about

25%, decreasing the utilisation even further (or even making the problem infeasible). Hence, the power of the charging stations can affect the vehicle utilisation when charging en route. The models in this work can measure the vehicle utilisation and assist the identification of economically viable routes for BEHVs.

6.4.3 Support of the selling process

There was no specific research found concerning the selection of the best BEHV variant through TCO minimisation. The most common topic is the comparison of ICEVs' and BEVs' TCO (Danielis et al., 2018; Davis & Figliozzi, 2013; Delucchi & Lipman, 2001; Tanco et al., 2019; Wu et al., 2015). In contrast, there are several solutions in the market that tries to assist on the fleet electrification process, identifying which route can be electrified (BEHV replace ICEV) and which is the best vehicle variant to serve this route (section 4.2). Due to this, there is a commercial desire to combine the here proposed model of BEHV variant selection and the comparison with ICEVs for complete assistance during the purchase or selling process. For now, the models optimise a fleet of BEHVs.

The vehicle selection was done based on three parameters: weight, volume and battery capacity. As long as the range of the demand is known by the customer, the load capacity is a straightforward decision based on the total demand and the fleet size given by the routing model. Fleet managers are already used to it, as it is the same for ICEVs. The only consideration is the change in weight capacity with the battery capacity, as discussed in section 6.4.2. Contrarily, the battery capacity is the main challenge for BEHVs' selection.

The best battery capacity for each case depended on the total time available, total energy consumption, battery capacity cost, depot electricity price and different charging stations' availability (depot, semi-public and public) and cost. This way, the vehicle selection not only satisfies the route energy demand, but the supply risk (associated with the energy supply and availability) is also assessed. The main driver is energy consumption, so it is important that the model focus on proving a reliable prediction for it. From it, combined with all cost parameters, it is possible to determine what is the optimal battery capacity. From the optimal battery, it is possible to know which would be the optimal vehicle variant to select.

For the urban case, the optimal battery capacity was 2.4 battery packs, given by the spreadsheet model. As there is no variant with two battery packs, three battery packs are selected. If there were two battery packs, it would be cheaper than three packs (Table 6.20).

Table 6.20: Difference between two vehicle variant options for the optimal battery capacity on the urban case.

2 Battery packs		
TCO	5 796 370	SEK
Extra charge required	12 590	Wh
EOL extra charge required	19 600	Wh
3 Battery packs		
TCO	5 835 882	SEK
Surplus charge amount	0	Wh
EOL extra charge required	1 384	Wh

However, the difference in the TCO of almost 40 000 SEK would likely not justify a downgrade for two reasons. First, there is a need to charge with two packs, whereas with three packs there is not. It can be argued that there are extra costs associated with managing the charging en route of vehicles, which are not included in the TCO calculation, that are higher than the savings of a downgrade over 10 years period. Second, as the battery degrades over time, extra charges en route are required to cope with the energy demand of the route. At the end-of-life of the battery (EOL), this would lead to more than 18 kWh extra charge en route per day for the smaller variant, increasing the overall cost.

The model also assists in understanding what are the impacts on vehicle selection of investing in charging infrastructure. In the regional case, the only charging strategy available was opportunistic charging at public charging stations. As a result, the optimal battery capacity was the lowest possible. With the time and charging station availability, four battery packs would be the lowest feasible battery pack, hence the lowest TCO. However, by investing in a DC charging station of at least 120kW at the depot, overnight charging becomes the best charging strategy and nine battery packs would be optimal battery (Table 6.21). Despite the extra investment, the overall TCO savings would be almost 23%. For the available variants (Table 6.6), the savings from investing in infrastructure would be around 20%.

Finally, it is possible to evaluate the impact on vehicle selection of the charging network. In the long-haul case, a hybrid charging strategy was selected. Again, overnight charging is the most cost-effective strategy. However, due to the charge power and cost of the available charging stations, the optimal battery capacity is

Table 6.21: Impact on the optimal battery capacity of investing in depot charging infrastructure in the regional case.

	No depot charge	**DC depot charge**
Optimal battery packs	4	9
TCO	12 051 091	9 298 042

extremely large to cope with the high energy consumption. Unless the availability of fast and affordable charging stations increases, the most cost-effective battery capacity will be the largest available. From the customer perspective, this increase is possible through subscriptions to other charging providers or negotiation of prices with the current ones.

6.4.4 Other applications for the models

Although this work was done to support decision making during the sales process, there are other areas within manufacturers, like Volvo, that can take advantage of the TCO model developed. TCO models can benefit the organisation as they give data for decision making, negotiation and understanding of cost factors for products to mention a few (Ellram, 1995; Ellram, 1994). Three possibilities are discussed: marketing, solution and service development, and vehicle research and development.

First, the model can be used for marketing purposes. For instance, it is possible to use the model to understand a customer type perspective and identify which are the most meaningful vehicle variants to advertise to them. The same logic can be applied to understand which markets to focus on. For example, as the model takes into consideration the charging infrastructure, new markets can be explored according to its maturity and the cost-effectiveness of operating an electric truck. Similarly, the TCO model can be used in the marketing of BEHV to justify the higher initial cost but lower TCO (Ellram, 1995).

Second, the model can also be used to develop new solutions or provide services. Volvo could assist customers to focus on decisions that would most benefit them from the insight Volvo gets from the TCO model of the customer operation (Ellram, 1994). For example, the model assists in deciding which charging infrastructure to invest in at the depot. If the route serves other locations owned by the customers, it is also possible to evaluate the financial impact of investing in semi-public charging stations. Moreover, the services of BEV fleet management, similar to the companies analysed in the market in the section 4.2, can be offered. Volvo could assist customers, e.g., on managing the fleet battery level, identifying the best charging location and which e-mobility service provider to subscribe to.

Lastly, the model can be used in the research and development phase of the vehicles. By understanding the customers manufacturers desire to address, it is possible to experiment with the battery capacity and price, for example, to understand if a new variant is required or viable. The data from the TCO model can help the OEM with the continuous improvement of the vehicle by identifying cost savings of the vehicles offered to the customer (Ellram, 1994).

7 Conclusion

This study focuses on creating a TCO model to help sellers and buyers of BEHVs to find the cost-optimal truck variant based on the route information. It explores how TCO models were done in previous literature and how they impact decision making in purchasing an electric truck. The selling process from Volvo's perspective is also considered and the TCO model created is customised for its needs.

To find the right variant, the model needed to solve a problem defined as a HEVRPTW problem. In a HEVRPTW problem, the optimal route is found based on a pool of electric vehicles available but it gets harder to solve as the problem grows, with more nodes and vehicle variants. Hence, three models were created: the MIP models (complete and simplified models), which give the most precise output; the hybrid model (MIP combined with a spreadsheet), which is flexible and can handle larger problems but is the least precise; and the ACO model, which can handle any problem size but is slightly less precise than the exact method. In cases where there is limited information from the customer, the problem might not be defined as a HEVRPTW problem due to a lack of data. The hybrid model includes a spreadsheet model that can be modified to calculate an approximated cost for a customer.

Three cases are built to perform an analysis of parameters of the TCO calculations and to check and demonstrate the reliability and validity of the models. Lastly, the supply chain impact of operating electric trucks is assessed by exploring literature and analysis of cases to give insight that might help transition to electromobility.

The output of the study can be summarised as follows:

- Three TCO models built: MIP model, hybrid model and ACO model
- Initial price and driver cost affect the TCO greatly in all cases
- Energy cost has the biggest effect on the TCO in high mileage cases but is

small in low mileage case

- The charging strategy is driven by the time available, battery cost, depot electricity price, and charging stations availability and cost
- The optimal battery capacity is not only driven by the energy consumption but also the charging strategy
- The battery capacity has trade-offs regarding the supply chain impact of BEHVs

The three models built should be able to cover a variety of situations when a customer is interested in buying an electric truck. From the analysis of cases with the complete model, the initial price of the BEHV and the driver cost are the parameters that affected the TCO calculation the most in all cases. In the low mileage case, those parameters account for over 95% of the TCO. However, in the high mileage cases, the proportion of those parameters decreases, and energy cost becomes the parameter that affects the TCO the most. Moreover, the models select the vehicle battery capacity based on the route energy demand and the most cost-effective charging strategy. The charging strategy is a balance of the cost of extra battery capacity with the time available, the owned charging stations (depot and semi-public) electricity price and public charging station availability and cost. The battery capacity also has an impact on the supply chain. Higher battery capacity will likely lead to higher range and operation cost but it decreases the weight capacity and increases the initial price. Besides, the range of a certain battery capacity heavily depends on the application and where it is used as the energy consumption changes in different contexts (such as weight, distance, speed, topography), as shown by the results of the cases.

Three cases are analysed with the complete TCO model: an urban, a regional and a long-haul distribution. In all cases, the problems are feasible with a single vehicle. The results of the complete model are validated with the hybrid and ACO models, which give similar results. All the parameters are deterministic and the majority of the input data was based on sources from recent years. Nevertheless, the values of these input data may not fully reflect the current post-pandemic situation with high inflation and interest rates. Similarly, policies and regulations are complex and change regularly, affecting the TCO (Breetz & Salon, 2018). If the high inflation and interest are not temporary, the input values should be updated to reflect this new scenario.

7.1 Implications

This work contributes to both research and theory. It makes use of VRP and energy consumption prediction (highly researched topics) to assist and reduce the uncertainty of decision-making regarding the purchase and sales of BEHVs, considering the supply risks of adoption of an electric fleet. Moreover, the main parameters that affect the TCO and the optimal battery capacity are identified. These insights have value for businesses. The proposed models assist in understanding the financial impact of the decisions regarding the transition to electromobility: battery size, infrastructure investment, charging strategy, optimal routes, feasibility and risks. Additionally, the data collected can be used as a reference when some information is missing.

7.2 Future research

There are a few limitations to this project. For example, all data used is deterministic. In real-world situations, many of the parameters the model requires may be stochastic, which may affect the recommendation of the optimal vehicle variant to purchase. There is no comparison with ICEV's TCO, which is common in literature and commercial solutions. Additionally, qualitative criteria are not considered in the TCO models presented here even though they are commonly present in a real-life situation and can be included in TCO models (Ellram & Siferd, 1993; Ferrin & Plank, 2002). Nonetheless, these points can drive the possible improvements of this work.

The model could be adapted to be able to deal with stochastic parameters (such as electricity price, resale price, service duration, and if a charging station is busy) and provide a statistically supported recommendation. Additional parameters can be specific per vehicle variant. For instance, vehicle system power is case specific, but it could be different for each heterogeneous truck within a single case. The model can be improved so it can manage ICEV variants as well. It could also calculate savings of CO_2 emissions when adopting a BEHV on a specific route, or savings by switching to a supplier with a renewable energy or set up by themselves. There are qualitative criteria listed in the literature (such as brand perception, drivers' satisfaction) and soft cost (such as adjacent costs or savings from purchasing a BEHV) that may be evaluated on their impact on the comparison of BEHVs and ICEVs. It would also be interesting to apply the models to larger problems and analyse their performance with themselves and against each other.

On top of that, battery degradation and non-linear charging models can be implemented. The charging infrastructure is more complex than just selecting AC or DC chargers. There is the possibility of investing in solar panels to charge the vehicles and reduce CO_2 emissions. For these cases, for instance, there is also a need for a charging management option when using the model, as done by commercial solutions of Electriphi and eIQ. Also, fleet managers usually optimise driver's utilisation for the whole week, not only a single day. The model could assist with it. As the problems become more realistic and complex, alternative algorithms to the exact method (MIP complete model) can be explored. The alternatives proposed in this thesis work are just a glance of the variety present in the literature. Lastly, instead of optimising only for TCO, the model could also optimise for CO_2 emissions or a supply chain KPI, such as vehicle's utilisation. This would make the model more flexible to the user's needs and it would be possible to evaluate the impact on the vehicle selection when changing these parameters.

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